# The Opponent Process Model of Problematic Pornography Use: Building a Foundation for Adaptive Digital Interventions

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## Abbreviations and Definitions

- AI: artificial intelligence
- $Amount$: length of time performing the behaviour (minutes)
- $a_{pd}$: pharmacodynamic compartment for the a-process (arb. units)
- $a_{pk}$: pharmacokinetic compartment for the a-process (arb. units)
- a-process: initial euphoric response to a behaviour, experience, or drug
- A-state: primary affective reaction of Solomon & Corbit's standard pattern of affective dynamics, in which summed a-processes are dominant
- AUTEC: Auckland University of Technology Ethics Committee
- BF: Bayes Factor
- BFRA: Behavioural Frequency Response Analysis
- $b_{pd}$: pharmacodynamic compartment for the b-process (arb. units)
- $b_{pk}$: pharmacokinetic compartment for the b-process (arb. units)
- b-process: compensatory opposite reaction to the a-process; a period of negative affect
- BSDS: Brief Social Desirability Scale
- B-state: affective after-reaction of Solomon & Corbit's standard pattern of affective dynamics, in which summed b-processes are dominant
- CSBD: compulsive sexual behaviour disorder
- $Dose$: compartment for hormonal and neurochemical concentrations following a 'dose' of digital technology use (arb. units)
- $Dose_{individual\ session}$: behavioural dose for a single behavioural session (arb. units)
- $Dose_{total}$: total dose of cumulative behavioural sessions (arb. units)
- $Duration$: period in which $Dose_{total}$ is assessed
- $E_{0_a}$: baseline effect for a-process (arb. units)
- $E_{max_a}$: maximum possible effect for a-process (arb. units)
- $EC_{50_a}$: half-maximal effect for a-process (arb. units)
- $\gamma_a$: sigmoidicity parameter for a-process (arb. units)
- $E_{0_b}$: baseline effect for b-process (arb. units)
- $E_{max_b}$: maximum possible effect for b-process (arb. units)
- $EC_{50_b}$: half-maximal effect for b-process (arb. units)
- $\gamma_b$: sigmoidicity parameter for b-process (arb. units)
- EMA: Ecological Momentary Assessment
- $f$: frequency of behavioural dose (min$^{-1}$)
- $Frequency$: the rate at which the behaviour is performed within a specific $Duration$
- GSES: Guilt and Shame Experience Subscale

- $H_{a,b}$: hedonic response compartment, representing the manifest affective response, calculated as the sum of the opposing a- and b-process pharmacodynamic compartments (arb. units)
- $H_{a,b}(t)_{single}$: value of hedonic response compartment at time $t$ for a single behavioural dose (arb. units)
- $H_{a,b}(t)_{total}$: value of hedonic response compartment at time $t$ for multiple behavioural doses (arb. units)
- HADS: Hospital Anxiety and Depression Scale
- HALO: Hormetic ALignment via Opponent processes
- ICD-11: International Classification of Diseases, 11th Edition
- $I_h$: hyperpolarization-activated currents in neurons
- IPU study: Internet Pornography Use study
- $k_{a,pk}$: clearance rate for a-process pharmacokinetic compartment ($a_{pk}$) (arb. units)
- $k_{b,pk}$: clearance rate for b-process pharmacokinetic compartment ($b_{pk}$) (arb. units)
- $k_{a,pd}$: clearance rate for a-process pharmacodynamic compartment ($a_{pd}$) (arb. units)
- $k_{b,pd}$: clearance rate for b-process pharmacodynamic compartment ($b_{pd}$) (arb. units)
- $k_H$: clearance rate for hedonic response compartment ($H_{a,b}$) (arb. units)
- $k_{Dose}$: clearance rate for $Dose$ compartment (arb. units)
- LNT: Linear No Threshold
- LWT: Linear With Threshold
- MFI: Multidimensional Fatigue Inventory
- mHealth: mobile health
- NOAEL: No Adverse Effect Level
- ODE: Ordinary Differential Equation
- PD: pharmacodynamics, i.e., the biological effect of neurochemicals on the body
- PK: pharmacokinetics, i.e., the movement of neurochemicals through the body
- $Potency$: level of immersion or engagement in a behaviour
- PPU: problematic pornography use
- SEMA3: Smartphone Ecological Momentary Assessment
- $t$: time elapsed since simulation began (minutes)
- $t_{sim}$: total simulation time (minutes)
- ULS-8: UCLA Loneliness Scale (short form)
- VTA: Ventral Tegmental Area
- WEIRD: Western, Educated, Industrial, Rich, and Democratic

## Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor used artificial intelligence tools or generative artificial intelligence tools (unless it is clearly stated, and referenced, along with the purpose of use), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

Nathan Henry, 28/10/2024

## Qualitative Statement of Primary Supervisor

Nathan has been primarily responsible for all aspects of the present research and all published articles. He has been responsible for at least 80% of the work on all his submitted and published pieces. He has been responsible for reviewing literature, developing hypotheses, designing the studies, obtaining ethics approval, organising materials, collecting data, data analysis, writing up the results, and writing the manuscripts for publication in a journal. My role, and that of my two fellow supervisors (Associate Professor Mangor Pedersen and Dr. Matt Williams), has been limited to advising and consulting with him on all these aspects of his PhD research in accordance with what is normally expected of a PhD supervisor.

Associate Professor Liesje Donkin, 28/10/2024

## Publications and Conference Presentations

Several publications and conference presentations arose from this thesis, including:

### Journal Articles

#### *Published*

1. Henry, N., Donkin, L., Williams, M., & Pedersen, M. (2022). mHealth technologies for managing problematic pornography use: Content analysis. *JMIR Formative Research*, *6*(10), e39869. https://doi.org/10.2196/39869
2. Henry, N., Pedersen, M., Williams, M., & Donkin, L. (2023). Behavioral Posology: A Novel Paradigm for Modeling the Healthy Limits of Behaviors. *Advanced Theory and Simulations*, *6*(9), 2300214. https://doi.org/10.1002/adts.202300214
3. Henry, N. I. N., Pedersen, M., Williams, M., Martin, J. L. B., & Donkin, L. (2025). Reducing echo chamber effects: An allostatic regulator for recommendation algorithms. *Journal of Psychology and AI*, *1*(1), 2517191. https://doi.org/10.1080/29974100.2025.2517191

#### *In Review*

1. Henry, N. I., Pedersen, M., Williams, M., Martin, J. L., & Donkin, L. (2024). A Hormetic Approach to the Value-Loading Problem: Preventing the Paperclip Apocalypse? *arXiv preprint arXiv:2402.07462*. https://doi.org/10.48550/arXiv.2402.07462
2. Henry, N. (2024). CRUD-Capable Mobile Apps with R and shinyMobile: a Case Study in Rapid Prototyping. *arXiv preprint arXiv:2409.00582*. https://doi.org/10.48550/arXiv.2409.00582
3. Henry, N. I. N., Pedersen, M., Williams, M., & Donkin, L. (2024). Quantifying the Affective Dynamics of Pornography Use and Masturbation: An Ecological Momentary Assessment Study. *Research Square preprint.* https://doi.org/10.21203/rs.3.rs-5094782/v1

### Conference Presentations

1. Henry, N. (2022). mHealth technologies for managing Problematic Pornography Use: A content analysis. *Rangahau Aranga: AUT Graduate Review*, *1*(3). https://doi.org/10.24135/rangahau-aranga.v1i3.119
2. Henry, N., Pedersen, M., Williams, M., & Donkin, L. (2024). Examining Possible Causal Relationships Between Pornography Use and Mental Wellbeing: An Ecological

Momentary Assessment Approach. Paper presented at Australasian Applied Statistics Conference, Perth, Western Australia, Australia.

3. Henry, N., Pedersen, M., Williams, M., & Donkin, L. (2024). Modeling frequency-based hormesis with behavioral posology: Theory and applications. Paper presented at Australasian Mathematical Psychology Conference, Perth, Western Australia, Australia.

**Conference Posters**

1. Henry, N., Pedersen, M., Williams, M., & Donkin, L. (2024). Behavioral count response analysis: A method for regulating repeatable AI behaviors. Paper presented at Technical AI Safety Conference, Tokyo, Japan.

**Co-Authorship Declaration for Published Manuscripts**

| | |
|---|---|
| **Chapter Number:** | 3 |
| **Manuscript Title:** | mHealth Technologies for Managing Problematic Pornography Use: Content Analysis |
| **Publication Status:** | Published |
| **Reference:** | Henry, N., Donkin, L., Williams, M., & Pedersen, M. (2022). mHealth technologies for managing problematic pornography use: Content analysis. *JMIR Formative Research*, *6*(10), e39869. https://doi.org/10.2196/39869 |
| **AUTHOR:** | **CONTRIBUTION:** |
| Henry | Conception and design; acquisition, analysis, and interpretation of data; primary author of manuscript. |
| Donkin | Supervision; critique of analysis; critical revision of manuscript. |
| Williams | Supervision; critique of analysis; critical revision of manuscript. |
| Pedersen | Supervision; critique of analysis; critical revision of manuscript. |

| | |
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| **Manuscript Title:** | Behavioral Posology: A Novel Paradigm for Modeling the Healthy Limits of Behaviors |
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| **AUTHOR:** | **CONTRIBUTION:** |
| Henry | Conception and design; model programming; analysis and interpretation of data; primary author of manuscript. |
| Pedersen | Supervision; critique of modelling; critical revision of manuscript. |
| Williams | Supervision; critique of modelling; critical revision of manuscript. |
| Donkin | Supervision; critique of modelling; critical revision of manuscript. |

| | |
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| **Reference (preprint):** | Henry, N. I. N., Pedersen, M., Williams, M., & Donkin, L. (2024). Quantifying the Affective Dynamics of Pornography Use and Masturbation: An Ecological Momentary Assessment Study. *Research Square preprint.* https://doi.org/10.21203/rs.3.rs-5094782/v1 |

| **AUTHOR:** | **CONTRIBUTION:** |
|---|---|
| Henry | Conception and design; acquisition, analysis, and interpretation of data; primary author of manuscript. |
| Pedersen | Supervision; critique of analysis; critical revision of manuscript. |
| Williams | Supervision; critique of analysis; critical revision of manuscript. |
| Donkin | Supervision; critique of analysis; critical revision of manuscript. |

I hereby declare that the co-authorship contributions stated above are accurate.

Nathan Henry, 28/10/2024

Associate Professor Liesje Donkin, 28/10/2024

## Declaration of Use of Artificial Intelligence

While artificial intelligence tools (specifically Microsoft Copilot and ChatGPT) were used in this thesis for grammatical suggestions and code debugging assistance respectively, these tools were used in a supplementary capacity only, similar to standard proofreading tools and programming resources. No artificial intelligence tools were used to generate original content, analysis, or conclusions within this thesis. All research, writing, analysis, and intellectual contributions are entirely my own work.

# Ethics Approval

The Auckland University of Technology Ethics Committee (AUTEC) provided ethical approval and advice for the studies carried out in this doctorate on 2 May 2023 (Application 23/80 - Problematic Pornography Use: Modelling Temporal Dynamics and Causal Effects on Mental Wellbeing). The approval letter can be found on the Open Science Framework website at the following link: https://osf.io/ck597/ (N. Henry, 2024a).

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No research is performed in isolation, and I have lost count of the number of times I have stumbled across a golden nugget of information while conversing with friends and fellow academics. For all those who have passed on their wisdom to me at AUT and elsewhere, wittingly or otherwise, I thank you. In particular, I want to thank Chris Krägeloh, Jim Phillips, Jamin Martin, Jacqueline Hannam, Beáta Bőthe, Takayoshi Ikeda, and Nicola Kayes for providing your ideas and support at critical junctures that helped to shape the direction of this thesis.

Finally, I want to thank my family, and in particular Mum and Dad, for fostering a love of science in me, and for your constant love and support over the years. And of course, to my wife Michelle, my rock during this time: thank you for being so incredibly patient with me while I pursued this crazy dream. You and Kyla mean everything to me.

# Abstract

Concerns are rising among mental health professionals and researchers about the effects of unrestricted pornography use, especially for those who experience moral incongruence related to pornography use. Mobile applications designed to address problematic pornography use (PPU) may provide a suitable alternative for those who would prefer not to discuss their pornography use with a therapist. However, there is a lack of literature examining the effectiveness of these applications.

To evaluate the available options for these individuals, I began by conducting a content analysis of mobile apps in the iOS and Google Play stores, focusing on their purpose, features, and popularity. From the 170 apps analysed, the most common features were relapse tracking, tutorials and coaching, accountability partners, content blocking and monitoring, and reward systems for abstinence progress. Yet while each feature appears to provide a unique benefit for reducing pornography use, there is a lack of evidence in the literature for the effectiveness of any of these apps in managing PPU.

A significant challenge in developing effective apps is the limited understanding of how, and over what timescales, pornography use may impact mental health. To address this gap, I proposed a novel modelling paradigm called behavioural posology, which quantifies the 'dose' of repeatable behaviours using four components: $Potency$, $Amount$, $Frequency$, and $Duration$. Using this paradigm, I simulated an opponent process model of pornography use, in which the behaviour triggers two opposing processes: a pleasurable a-process and a negative b-process. In this model, moral incongruence is a moderating factor that amplifies the b-process, leading to more rapid allostasis and greater harm to mental health. Using simulated data from a pharmacokinetic/pharmacodynamic model of pornography use, the model accurately predicted several features of behavioural addiction, such as hedonic allostasis, withdrawal, and apparent tolerance.

To test the empirical accuracy of the opponent process model of pornography use, I conducted an Ecological Momentary Assessment (EMA) study to quantify the temporal dynamics produced by pornography use. EMA data was collected from 22 participants, who were divided into low and high moral incongruence groups. Results showed that pornography use and masturbation were followed by negative affective states that decayed in an approximately exponential fashion, as predicted by the opponent process model. Participants with high moral incongruence experienced increases in guilt, shame, loneliness, and difficulty thinking, along with decreases in mood and relationship connectedness, either before or after sexual episodes. Additionally, opponent process dynamics were observed in the mood of high moral incongruence

participants, suggesting a potential mechanism that may explain the link between PPU and depressed mood for certain individuals.

In conclusion, behavioural posology was developed as a theoretical framework for hypothesising and testing the temporal dynamics of addictive and compulsive behaviours such as pornography use. As such, this research provides new insights into the potential causal mechanisms behind PPU, which may help to guide the future creation of mobile applications for treating PPU that are adaptable to the individual's momentary needs.

## Chapter 1: Introduction

Problematic pornography use (PPU), defined here as excessive or compulsive use of pornography despite negative perceived consequences, is linked to various mental health conditions such as depression and anxiety, as well as interpersonal issues including loneliness, relationship dissatisfaction, and marital difficulties (Borgogna & McDermott, 2018; Butler et al., 2018; Guidry et al., 2020; Hanseder & Dantas, 2023; Harper & Hodgins, 2016; Huțul & Karner-Huțuleac, 2024; Miller et al., 2019; Vieira & Griffiths, 2024). Many believe that Internet pornography can be addictive – a view that is pervasive on online forums such as the r/NoFap subreddit on the website reddit.com, which contains a growing community of users sharing personal stories, strategies, and support for overcoming pornography addiction (Burnett, 2022; Chasioti & Binnie, 2021; *NoFap® Porn Addiction Recovery*, 2022).

However, the academic debate over the existence of 'pornography addiction' is polarised. Some researchers have argued that pornography addiction should be recognised as a legitimate behavioural addiction in a similar vein to online gambling addiction (Hilton Jr, 2013; Love et al., 2015), which is now officially classified as a disorder in the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) and International Classification of Diseases (ICD-11) (Pistre et al., 2023). On the other hand, some researchers believe that the brain networks associated with pornography use are distinct from the networks that are activated by addictive processes. For example, a recent meta-analysis of resting-state functional connectivity studies suggested that substance use disorders and behavioural addictions are characterised by dysfunctions that can be localised to separate brain networks (Tolomeo & Yu, 2022). Furthermore, critics have contended that labelling excessive pornography use as an addiction runs the risk of pathologizing normal sexual behaviour, potentially leading to high numbers of false positive diagnoses of addiction (Klein et al., 2019; Wakefield, 2012). Many scientists are in favour of an alternative model, in which PPU is treated as an impulse-control disorder (Bőthe, Koós, et al., 2023; Kraus et al., 2018; Lewczuk, Wizła, et al., 2022), and where psychosocial problems are caused by one’s feelings of moral incongruence towards pornography use – in essence, a feeling of cognitive dissonance where one’s pornography use conflicts with one’s beliefs that using pornography is morally wrong (Grubbs & Perry, 2019).

Yet a glaring issue remains: the psychological mechanisms linking pornography use and negative mental health have not yet been confirmed or quantified. There is a large volume of correlational data in the literature indicating the presence of these links, while the number of longitudinal studies assessing the use and effects of pornography over time is increasing steadily (e.g., see Bőthe et al., 2022; Chen, Jiang, Luo, et al., 2022; Dawson et al., 2019; Grubbs et al., 2021; Kohut & Štulhofer, 2018; Leonhardt & Willoughby, 2018; Mattebo et al., 2018; McGraw et al., 2024; Milas et al., 2020; Muusses et al., 2015; Perry, 2017b; Perry & Davis, 2017; Šević et al., 2020; Vaillancourt-Morel et al., 2023; Wright, 2012, 2013, 2023). However, there is little longitudinal data being produced on a short-enough timescale and with sufficient temporal frequency to quantify the temporal dynamics associated with pornography use on a momentary basis, although some progress is being made in this area (Bőthe, Baumgartner, Schaub, et al., 2020; Bőthe et al., 2021; Stark et al., 2024; Vaillancourt-Morel et al., 2020, 2024; Wordecha et al., 2018). Without a better understanding of these dynamics, we cannot determine whether pornography use causes the associated mental health issues, whether the relationship is reversed, or if the relationship is bidirectional. Until we have high-frequency longitudinal data that can demonstrate the nature of these relationships, discussions about pornography's true impact on mental health will remain speculative and inconclusive.

In the course of this thesis, I developed a novel modelling paradigm called behavioural posology, with the aim of quantifying the effects of behaviours as though they were drugs. As I will show, combining this paradigm with high-frequency longitudinal data, such as that provided by Ecological Momentary Assessment, or EMA (Shiffman & Stone, 1998), allows us to better quantify the temporal dynamics directly before and after pornography use, providing new insights into the potential causal pathways between pornography use and mental health. It is hoped that this will bring us closer to understanding the true symptomology of PPU, along with its unique psychological and neurobiological markers, which may aid in classifying PPU as either an obsessive-compulsive disorder, impulse-control disorder, or addiction. In turn, this will facilitate the development of more effective and scientifically accurate PPU therapies that can target the underlying mechanisms driving the behaviour, and that can be delivered through in-person therapy or via mobile platforms.

Currently, there are several mobile applications that purport to provide users with tools to eliminate ‘pornography addiction’. Many of these applications could potentially be improved using the latest findings from the literature on PPU. In fact, as I discovered in reviewing the literature, while some research is being done on therapeutic interventions using mobile applications (Bőthe, Baumgartner, Schaub, et al., 2020; Bőthe et al., 2021; Stark et al., 2024), there is a complete lack of literature to validate the claims of currently available mobile apps. This is not to say that these apps should be discarded; indeed, many of them provide what appears to be valuable therapeutic assistance for those struggling to control their pornography use. However, there is an urgent need for mobile applications designed to safely assist those seeking to abstain from pornography use, that are also built on the latest theoretical advancements in this field.

My efforts to develop such an application were the original inspiration for this thesis. In 2021, I used the shinyMobile package in R (Granjon et al., 2024; R Core Team, 2022) to create

Harden, a mobile app that allowed the user to perform a self-managed EMA, complete with automated self-analysis tools to assess their pornography use, with the aim of abstinence (N. Henry, 2024b). Although I may return to this project in future, for now, this thesis represents the culmination of my work on this topic. It also represents my initial attempt to quantify the causal links between pornography use and mental health conditions such as depression. While progress has been made, much work still needs to be done in this area.

## Aims

The broad aim of this thesis was to develop a conceptual and mathematical framework to better understand the temporal dynamics of PPU, in the hopes that this would also allow us to assess the temporal directionality of PPU in relation to various mental health indicators, ultimately paving the way for improved mobile therapies for PPU in future.

My main objectives were:

1) To assess the current state of mobile app therapies for treating PPU, highlighting needs for future research on therapeutic options.
2) To evaluate whether opponent process theory is a suitable framework for quantifying the temporal dynamics of pornography use.
3) To determine the direction of causality between pornography use and other mental health variables.
4) To evaluate whether an opponent process model of pornography use can be used to identify safe dose limits for pornography use.

To achieve these aims, I designed a study to capture high-frequency longitudinal mental health data relative to pornography use using a mobile app-based EMA design. It is hoped that the models produced from this data may become tools for clinicians and researchers to help individuals understand and regulate their pornography consumption, and that similar models could eventually be applied to other behavioural disorders such as gambling, Internet, and gaming addictions.

## Thesis Structure

This thesis combines a literature review (Chapter 2), a content analysis of currently available pornography apps (Chapter 3), an overview of the research design (Chapter 4), a simulation study using the behavioural posology paradigm (Chapter 5), an EMA study of pornography users (Chapter 6), and an integrative discussion tying together the main findings from each study (Chapter 7). A brief overview of each Chapter follows:

- Chapter 2: Provides a literature review covering the key research on different models of PPU, along with current therapeutic options and technological interventions for PPU. This lays the theoretical groundwork for the remaining Chapters.
- Chapter 3: A published article that contains a content analysis describing apps currently available on the major mobile app stores for reducing pornography addiction.
- Chapter 4: Contains an overview of the research design, with a focus on introducing the basics of pharmacokinetic/pharmacodynamic modelling, the conceptual foundations of the behavioural posology modelling paradigm and opponent process theory, and the design of EMA studies. This lays the methodological foundation for the following Chapters.
- Chapter 5: A published article that introduces the opponent process model of pornography use and the behavioural posology paradigm. This is a simulation-based study that outlines the theoretical basis for performing the EMA study in Chapter 6.
- Chapter 6: An article submitted for publication, containing the results of an observational EMA study that aims to quantify the temporal dynamics of pornography use and masturbation, using the opponent process model as a theoretical framework. This study was called the Impact of Pornography Use (IPU) study.
- Chapter 7: An integrative discussion that outlines the main findings from each study in the context of the literature, along with the limitations and weaknesses of each study, and proposed future research.

Where applicable, Chapters are presented in their published format, without edits unless stated. Short preludes are included before each article to contextualise the article within the thesis. All references including those from each manuscript have been combined in a single list at the end of the thesis, followed by Appendices that are relevant to each study.

## Chapter 2: Literature Review

### Problematic Pornography Use (PPU)

Internet pornography use is becoming increasingly common worldwide, having been accelerated by the rapid proliferation of the Internet and personal computing devices, along with widespread cultural acceptance of pornography (Carroll et al., 2008; Price et al., 2016). A national survey of a representative sample of 688 heterosexual Danish adult men and women found that 97.8% of men and 79.5% of women in Denmark had ever watched pornography; of these, 82.5% of men and 33.6% of women stated they had watched pornography in the last month (Hald, 2006). More recently, a cross-sectional study of a nationally representative sample of 1,985 Australians aged 15-20 years found that 86% of young men and 69% of young women had viewed pornography, with 54% of male participants and 14% of female participants reporting weekly usage (Crabbe et al., 2024). However, increased rates of depression and anxiety have been reported in people struggling with problematic pornography use (PPU) – defined here as compulsive, dysregulated, or excessive pornography use (Grubbs, Perry, et al., 2022) – particularly in those users who perceive pornography as being morally repugnant (Grubbs & Perry, 2019). The preregistered International Sex Survey, a study across five continents and 42 countries, found that 3.2% of participants were at risk of experiencing PPU based on the Problematic Pornography Consumption Scale (PPCS), a scale for measuring PPU risk across diverse populations (Bőthe, Nagy, et al., 2024), indicating that PPU impacts a significant portion of the population.

Pornography can be defined as “material (text, audio, video, etc) that (i) creates or elicits sexual feelings or thoughts and (ii) contains explicit exposure or descriptions of sexual acts involving the genitals, such as vaginal or anal intercourse, oral sex, or masturbation” (Bőthe, Tóth-Király, Demetrovics, et al., 2020, p. 344). Pornography has also been described as a ‘supranormal stimulus’ due to the hyper-novel range of pornographic content available, coupled with the augmented features of its performers (Barrett, 2010; Hilton Jr, 2013). This has raised concerns regarding the effects of pornography on users, particularly during adolescence, in terms of sexual attitudes and mental health (Hilton Jr, 2013, p. 201; Owens et al., 2012; Tinberge, 1954). There is growing evidence of a link between chronic pornography use and social problems such as increased violence towards women (sexual and non-sexual) and relationship and intimacy problems, although the causal link between these factors remains unclear (Lucumi et al., 2024; Mestre-Bach et al., 2023). There is also correlational evidence that chronic pornography consumption is linked to increased rates of erectile dysfunction, premature ejaculation, and alterations to one’s genital anatomy (Lucumi et al., 2024). The compulsion to use pornography can also have acute consequences; for example, there is a growing number of reports of traffic fatalities that were caused by distracted driving due to pornography use (Newton et al., 2022; Oviedo-Trespalacios & Phillips, 2021), and of workplace dismissals due to use of pornography in the workplace (Cameron, 2012; Chelliah, 2014).

For most people today, avoiding the Internet as a means to reduce pornography exposure is not possible due to the wide range of everyday activities, both professional and social, that require Internet access (Mihajlov & Vejmelka, 2017). This makes abstinence from pornography a more challenging proposition today than in a pre-Internet world (Young et al., 1999). Internet users only need to perform a web search to obtain unrestricted access to an enormous volume of free pornography content, with near-complete anonymity (Cooper, 1998; Cooper et al., 1999; Wolak et al., 2007). There is also an increasing volume of sexual content on non-sexual platforms, such as YouTube, Instagram, and TikTok. Although this content is technically not ’pornographic’, it often portrays overtly sexualised content to increase traffic (Bunta, 2021). In addition, news media, social media, and other Internet-based platforms are saturated with sexual imagery and content, driven by free-market forces and machine learning algorithms that target sexual advertising content at users (Cooper et al., 1999; Simon & Greitemeyer, 2019). This is problematic, since widespread access to the Internet may lead to unwanted exposure to sexual content (Wolak et al., 2007), particularly for vulnerable populations such as children and those struggling with PPU.

**Causal Relationships Between PPU and Mental Health Outcomes**

In addition to its links to negative mental health outcomes, pornography use has been linked to various social detriments, including decreased relationship satisfaction, heightened loneliness, and difficulties with social wellbeing (Bridges & Morokoff, 2011; Butler et al., 2018). Cross-sectional studies have indicated that self-perceived addiction to pornography mediates the relationship between use and reduced relationship satisfaction, with religiosity and gender further moderating this effect (Floyd & Grubbs, 2022; Willoughby & Dover, 2022). Individuals with PPU often report greater loneliness and fear of intimacy, although those who use pornography primarily for enjoyment, rather than to cope with negative emotions, appear to exhibit similar social wellbeing to non-users (Maitland & Neilson, 2023). Difficulties in emotion regulation are also positively correlated with PPU, with loneliness possibly mediating this relationship (Cardoso et al., 2023). Moreover, increased loneliness and poorer emotional regulation can predict higher levels of pornography use (Mestre-Bach & Potenza, 2023b), potentially suggesting a bidirectional relationship where loneliness may lead to increased pornography use, which in turn may increase feelings of loneliness.

There is a lack of longitudinal data that can quantify the directionality and valence of these relationships. In fact, masturbation is broadly considered to have some positive effects on relaxation, stress reduction, and sleep quality (Burri & Carvalheira, 2019; Fahs & Frank, 2014; Lastella et al., 2019), as well as enhancing some women's ability to experience orgasm (Hurlbert & Whittaker, 1991; Rowland et al., 2019, 2020). Additionally, pornography use, masturbation, or both combined may also form a component of sexual development for adolescents and young adults learning about their sexuality (Atwood & Gagnon, 1987; Constantine, 1981; J. K. Davidson & Darling, 1993; Pinkerton et al., 2003; Rowland & Cooper, 2017; Saliares et al., 2017).

However, it appears that the outcomes associated with pornography use are heavily dependent on the context in which it is used. For example, excessive solo pornography use within a relationship is generally associated with lower relationship and sexual satisfaction, less attraction to one's partner, increased divorce proneness, and reduced relationship stability (Willoughby et al., 2016; Willoughby & Dover, 2022). A review of the impact of Internet pornography use on marriage and family found that online sexual activity, including pornography use accompanied by masturbation, was a common factor in separation and divorce for many affected couples, suggesting that the accessibility of pornography on the Internet played a facilitating role in these behaviours (Manning, 2006). Other studies have found that in cases where pornography is only used by one partner, problems are often observed related to male arousal, decreased sexual interest in one's partner, unrealistic sexual expectations, increased insecurity, decreased sexual satisfaction, and negative female self-perception (Daneback et al., 2009; Kohut et al., 2017; Ruffing et al., 2022; Willoughby et al., 2016). Higher combined levels of religiosity and partner-perceived frequency of pornography use are also linked to worse relationship satisfaction (Major et al., 2024; Ruffing et al., 2022), with spousal religiosity appearing to intensify the negative effects of pornography viewing on marital satisfaction, despite spousal religiosity being otherwise positively related to marital satisfaction (Perry, 2016). This may indicate that lack of communication about pornography use is one factor that may be harmful to relationship stability, although it is also possible that pornography use differences between partners may alter patterns of interaction between partners (Willoughby et al., 2016). Sun et al. (2016) have also argued, based on their survey analysis of 487 college men in the United States, that pornography use shapes the sexual scripts influencing men's real-world sexual behaviours, with increased consumption linked to incorporating pornographic acts during sex, using pornography for arousal, and experiencing performance and body image concerns, while reducing enjoyment of intimate behaviours. In summary, there are several plausible mechanisms for a bidirectional causal relationship between PPU and relationship dissatisfaction.

Overall, a greater proportion of men consume pornography than women, and at a higher average frequency (Böhm et al., 2015; Crabbe et al., 2024; Hald, 2006). Peterson & Hyde (2010) performed a meta-analysis of the literature on gender differences in sexuality, and found that masturbation frequency and pornography use are key areas where men and women differ the most in terms of sexual practices and attitudes. Men are also more likely to be exposed to pornography at a younger age (Hald, 2006). This suggests that any mental health issues stemming from pornography use are more likely to disproportionately affect men, particularly given that men are more likely to have negative attitudes towards seeking psychological treatment (Komiya et al., 2000). However, one study found that while women are more likely than men to seek treatment for PPU based on the amount of pornography they use, women with PPU are also likely to have higher levels of negative symptoms associated with PPU (Lewczuk et al., 2017). One possible hypothesis is that female pornography use carries greater stigma than male use, as it is less common among women, leading to increased guilt and shame. While more research is needed in this area, it is clear that both genders are impacted by PPU, albeit in different ways.

Qualitative studies have also observed a possible link between pornography use and 'brain fog', a condition characterised by difficulty in thinking clearly and maintaining attention (Palazzolo & Bettman, 2020; Sangeado, 2016). This and similar phenomena often appear on online forums such as the r/NoFap subreddit (*NoFap® Porn Addiction Recovery*, 2022) but have been less well studied. For example, the idea of 'post-nut clarity' has grown in popularity, describing post-coital regret about having sex or masturbating (Orchard & Sangaraganesan, 2022). Similar reported phenomena in the literature include post-orgasmic illness syndrome (POIS) (Bolanos & Morgentaler, 2020; Paulos & Avelliino, 2020; Reisman & Tripodi, 2022; Waldinger & Schweitzer, 2002), post-coital tristesse (Reisman & Tripodi, 2022), and post-coital dysphoria (Colombo & Concone, 2019; Schweitzer et al., 2015; Taverna et al., 2022). Of these phenomena, POIS appears to be the most comprehensively researched and defined. Reisman & Tripodi (2022) describe POIS as a cluster of flu-like and allergic symptoms that begin shortly after ejaculation and may last from minutes to days[1]. POIS symptoms may include severe fatigue, emotional trauma, reduced concentration, irritability, confusion, poor judgment, memory issues, anxiety, insomnia, depression, mood swings, and low energy (Reisman & Tripodi, 2022; Waldinger & Schweitzer, 2002). Reisman & Tripodi (2022) further suggest that, when no physical cause is evident, psychological factors such as guilt or religiosity may play a role, suggesting it is possible that moral conflicts related to pornography use or sexual behaviour could trigger or worsen POIS symptoms. However, research on this connection is limited, likely because POIS is generally viewed as an allergic or autoimmune condition. Further research is needed to fully understand the potential interplay between psychological and physiological aspects of POIS, which could offer insights into the nature and causes of PPU for some individuals.

[1] Similar symptoms can also occur in women, with female orgasmic illness syndrome (FOIS) now being a recognised, albeit rarer, condition (Goldstein & Komisaruk, 2018; Reisman & Tripodi, 2022).

Despite the growing volume of cross-sectional evidence, no longitudinal study has yet been designed that can quantify causal relationships between pornography use and negative mental health symptoms. While causality is generally tested experimentally – for example, in a randomised controlled trial (RCT) – ethical and practical difficulties associated with creating a control group for pornography users make this a challenging prospect. Yet there may be alternative ways to quantify potential causal mechanisms without using such methods. I explore this possibility further in Chapter 6.

### Is PPU an Impulse-Control Disorder, Obsessive-Compulsive Disorder, or Addictive Disorder?

As outlined previously, it has long been a subject of debate as to whether PPU should be conceptualised as an addictive disorder, an obsessive-compulsive disorder, or an impulse-control disorder – or even if it should be considered a disorder at all (Gold & Heffner, 1998; Grubbs, Grant, et al., 2020). Hypersexual disorder was proposed as a diagnosis for inclusion in the DSM-5, but was ultimately rejected due to concerns about insufficient empirical evidence, potential for misuse of the diagnosis, and debates about whether the condition represents a distinct disorder (Carvalho et al., 2015; Kafka, 2010; Kor et al., 2013; Reid et al., 2012; Reid & Kafka, 2014; Winters, 2010). Compulsive Sexual Behaviour Disorder (CSBD) is currently classified as an impulse-control disorder (code 6C70) in the ICD-11, and is defined as "a persistent pattern of failure to control intense, repetitive sexual impulses or urges, resulting in repetitive sexual behaviour over an extended period (e.g., six months or more) that causes marked distress or impairment in personal, family, social, educational, occupational or other important areas of functioning" (Kraus et al., 2018). CSBD and hypersexuality have both been shown to have strong positive associations with PPU (Bőthe et al., 2019; Bőthe, Potenza, Griffiths, et al., 2020).

Yet it remains controversial whether PPU should be labelled an addiction or merely be included as a subtype of CSBD, as it is currently in the ICD-11 (Kraus et al., 2018). Others have suggested it should be classified at the intersection between compulsive sexual behaviour and Internet addiction (M. D. Griffiths, 2012; Ince et al., 2024; Love et al., 2015). Another alternative that has been proposed is classifying PPU under "Other Specified Disorders due to Addictive Behaviours" (code 6C5Y) in the ICD-11, although there remains a lack of established criteria for diagnosing behaviours in this category (Bőthe et al., 2019; Bőthe, Potenza, et al., 2024). More research is needed to understand the physiological mechanisms underlying PPU, along with appropriate diagnostic criteria and treatment approaches for CSBD (Lew-Starowicz & Coleman, 2022).

The debate in part focuses on the symptomology and aetiology of PPU, and how it aligns with different behavioural frameworks: addictive behaviours are characterized by reward-seeking, dependence, tolerance, and withdrawal symptoms during abstinence; impulsive behaviours result from poor self-control and a craving for immediate gratification; and compulsive behaviours are performed to reduce anxiety or discomfort, often repetitively (Bőthe et al., 2019; Lee et al., 2019). Yet there is much overlap between these concepts, with impulsivity and compulsivity both including aspects of disinhibition; further, addiction appears to include aspects of both impulsivity and compulsivity (Lee et al., 2019; Mick & Hollander, 2006). Indeed, a common feature across these conditions is the person's persistence with the behaviour despite its interference with one's personal goals and wellbeing. Hence, these categories may not necessarily be mutually exclusive (Bőthe et al., 2019), and it is possible that PPU may be more accurately defined using a combination of these categories.

One attempt to simplify this complexity was made by Griffiths (2005), who laid out six criteria for a behaviour to be labelled as 'addictive': salience, mood modification, tolerance, withdrawal symptoms, conflict, and relapse. Griffiths went on to propose that Internet sex addiction, which includes consumption of online pornography, may be a sub-form of Internet addiction with some (but not all) of the characteristics of sex addiction in real life, and noted that a clear diagnostic framework was still required to assess this pathology clinically (M. D. Griffiths, 2012). Several of the symptoms proposed in Griffiths' six component model of addiction have been observed anecdotally in forums such as the r/NoFap and r/pornfree subreddits on the website reddit.com (Burnett, 2022; Chasioti & Binnie, 2021; Prause & Binnie, 2023), but little research has been undertaken to validate these symptoms. Fernandez et al. (2021b) performed a qualitative analysis of abstinence journals taken from Reboot Nation, an online 'rebooting' forum for people seeking to quit pornography use. Many participants encountered "habitual behaviour patterns and/or cravings triggered by a multiplicity of cues for pornography use", which made sustained abstinence challenging (Fernandez et al., 2021b, p. 711). In the same study, close to one-third of participants reported a temporary period of symptoms during abstinence - known as the 'flatline' by members of the r/NoFap community – including decreased libido, low mood and a sense of disengagement (Fernandez et al., 2021b). It is plausible that these symptoms result from pornography withdrawal, which would fit with the addiction model criteria. However, no scientific study has been able to confirm that the flatline exists nor define a set of symptoms that accurately describes this condition.

Many researchers believe that care must be taken not to misdiagnose or over-pathologise people who may self-identify as being 'sex addicts' or 'porn addicts', and who may feel intense guilt and shame due to their behaviours, yet may be better treated for other mental health problems such as anxiety and depression that may contribute to PPU (Kraus et al., 2018). There are also concerns about the unregulated nature of the treatment industry for pornography addiction, which includes inpatient facilities and pharmaceutical interventions, but is often lacking in scientific validation; some programs are also affiliated with religious groups, raising questions about potential conflicts of interest (Ley et al., 2014), as well as the effectiveness and ethics of these practices. However, I agree with Hilton & Watts (2011) in saying that it is irresponsible not to conclude that there is compelling evidence for a causal relationship between pornography use and negative effects on both individuals and relationships. Despite largely correlational evidence, the potential causal links between PPU and negative mental health outcomes should be further investigated empirically. Pathological gambling has long been recognised as an addiction (Raylu & Oei, 2002), and the mental health harms associated with PPU are potentially similar in terms of affective magnitude, even if the symptoms differ. Thus, irrespective of whether PPU is an addictive disorder, it should still be addressed with an appropriate level of concern.

### The 'Moral Incongruence' Model of PPU

Associations between pornography use and depression, anxiety, loneliness and guilt have been detected in several correlational studies (Borgogna & McDermott, 2018; Butler et al., 2018; Harper & Hodgins, 2016; Kraus et al., 2015). Many of these associations appear to be moderated by demographic factors such as religiosity, even after statistically controlling for baseline religious and spiritual struggles (Grubbs et al., 2017), indicating a link between one's moral perception of pornography use and mental or spiritual problems stemming from such use (Grubbs & Hook, 2016). This makes sense, given that the avoidance of improper sexual activity is often considered a key part of spiritual pursuits (Grubbs et al., 2017). Indeed, while other factors such as relationship status, gender, and sexual identity may be salient, there is a growing body of evidence to suggest that moral incongruence – a form of cognitive dissonance where the individual believes that pornography use is morally wrong and thus experiences feelings of guilt and shame following use – is the primary predictive variable for adverse mental health outcomes associated with PPU (Brand et al., 2019; Fisher et al., 2019; Grubbs, Perry, et al., 2019a; Grubbs, Lee, et al., 2020; Grubbs, Floyd, et al., 2022; Grubbs & Kraus, 2021; Grubbs & Perry, 2019; Lewczuk et al., 2020, 2021; Perry, 2018b).

The development of this 'moral incongruence' theory of PPU, which appears to be a point of convergence in the literature, has accelerated over the past 15 years. Twohig et al. (2009) ran an online survey of 84 college-age males, and found that while approximately 20%-60% of the sample who viewed pornography believed that their use was problematic, negative outcomes did not increase with a higher frequency of viewing. The authors proposed that "If viewing is contrary to an individual's values or moral base, then even one instance would be experienced as problematic" (Twohig et al., 2009, p. 263). This was validated by Kraus et al. (2016), who recruited 1,298 male pornography users to complete questionnaires on their sexual behaviours, and identified that 29% of men in this study who reported an interest in treatment for pornography use did not meet the criteria for hypersexuality based on the Control subscale of the Hypersexual Behaviour Inventory (Kraus et al., 2016). This indicates that moral incongruence was likely a key predictor of treatment seeking behaviour in this subset of participants, as their pornography use was not deemed excessive by an objective external measure.

In recent years, Grubbs and associates have further developed the theoretical framework of moral incongruence (Grubbs, Exline, et al., 2015; Grubbs, Kraus, et al., 2019; Grubbs & Perry, 2019), culminating in the development of an integrative model for perceived problems due to moral incongruence. This explains how conflicts between an individual's sexual behaviours, such as pornography use, and their moral or religious values can lead to distress, feelings of shame, and the belief that they have a problematic sexual behaviour, even when their behaviour is not objectively excessive (Grubbs, Perry, et al., 2019a). Hence, moral incongruence theory provides an alternative model to 'pornography addiction' for explaining how problems related to pornography use – including feelings of addiction – may be explained by the moral incongruence between one's beliefs and one's sexual behaviours.

This model has been criticised for being too narrow in scope, focusing mainly on intrapersonal difficulties from conservative sexual ideals, rather than interpersonal issues and other broader effects (Brand et al., 2019; Fisher et al., 2019; Grubbs, Perry, et al., 2019b; Kraus & Sweeney, 2019; Vaillancourt-Morel & Bergeron, 2019; Walton, 2019; Willoughby, 2019; Wright, 2019). It has also been suggested that the model may not generalise outside of the United States, as it relies heavily on data from participants in that region[2] (Grubbs, Perry, et al., 2019b). However, it is perhaps the most cohesive model of PPU currently available in the literature. Consequently, it has served as the foundation for a significant proportion of recent scholarly investigations in this domain.

The moral incongruence model of PPU focuses heavily on the religious aspect of moral incongruence, which doesn't necessarily capture all pathways to PPU (Grubbs, Perry, et al., 2019b). However, the relationship between religiosity, moral incongruence, and pornography use has been identified in numerous studies. Nelson et al. (2010) highlighted that religious individuals in particular may experience an internal struggle when using pornography while also believing it is morally wrong, leading to feelings of cognitive dissonance. Grubbs, Exline, et al. (2015) found that religiosity positively predicted perceived pornography addiction, even after accounting for

[2] The United States has a higher proportion of Western, Educated, Industrial, Rich, and Democratic (WEIRD) individuals compared to other countries globally, raising questions of how well psychological findings from this population can be generalized to other societies (Henrich et al., 2010).

covariates like self-control, neuroticism, and pornography use frequency. These studies indicate that religious beliefs about the morality of sexuality and pornography use is likely to play a role in one's perceived addiction to pornography; indeed, several religions teach that sexual desires and behaviours are only morally acceptable within monogamous, heterosexual marriages (Perry, 2017a).

Therefore, it appears that while moral incongruence related to pornography use is not exclusive to religious individuals, religiosity may be a moderating factor between pornography use and feelings of moral incongruence, along with feelings of psychological distress and perceived addiction to pornography (Grubbs & Perry, 2019). In turn, pornography use may have an impact on religious salience, complexifying the relationship between these two constructs. Notably, Perry (2017) found that overall, viewing pornography may reduce religiosity over time and increase religious doubt. However, the relationship was not necessarily linear; more frequent pornography use initially decreased religiosity, but beyond a certain frequency (about two to three times a month), religiosity levelled off or even increased slightly. Similar trends were observed for both men and women, though worship attendance was more negatively affected for men (Perry, 2017a). Hence, while more research is needed to determine the causal nature of these findings, the evidence for a link between religiosity and moral incongruence towards pornography use is strong.

Recent research has explored how moral disapproval may contribute to self-perceived addictions across various behaviours, including drug use. A registered report by Grubbs et al. (2022) surveyed a large sample in the United States (N = 4,363) and found significant evidence for an interaction model of moral incongruence (where moral incongruence = moral disapproval × frequency of use), in which pornography use can lead to profound distress and self-perceived addiction if cognitive and moral dissonance is experienced from use (Grubbs, Floyd, et al., 2022). Interestingly, a similar model was found to be significant for the interaction between moral incongruence, gambling, and self-perceived gambling addiction, but when tested on substances and tobacco, the model was not significant; a similar model for alcohol and marijuana use proved inconclusive. Hence, there may be several behaviours that, when combined with moral disapproval of that behaviour, can lead to self-perceived addiction and distress. However, the study's lack of significant findings for the application of the moral incongruence model to substances like tobacco and alcohol makes sense, given that these substances are more socially accepted in the United States. In addition, while the moral incongruence model may be predictive of behaviour-related distress, it doesn't necessarily account for the underlying neurohormonal dynamics that may be associated with these behaviours – in particular, the dynamics of the sexual response cycle, which is associated with sexual excitement, orgasm, and recovery (Masters & Johnson, 1966; McNabney et al., 2020). This highlights the need for more research to distinguish between the effects of moral incongruence and the mechanisms of actual addiction, if these are indeed separate mechanisms leading to distress.

The literature also shows a potential dose-response relationship between pornography use and negative mental health outcomes, although the relationship is complex. When examining this relationship, we must consider the possibility of an interaction between frequency of use and moral incongruence. One cluster-analytic study, using data from an online convenience survey sample of 830 North American adults, found three distinct profiles of pornography users: recreational (75.5%), highly distressed non-compulsive (12.7%), and compulsive (11.8%) (Vaillancourt-Morel et al., 2017). Women and dyadic users were more prevalent in the recreational profile, which reported higher sexual satisfaction, while men and solitary users were more common in the compulsive profile, which experienced lower satisfaction and higher compulsivity and avoidance than the other profiles (Vaillancourt-Morel et al., 2017). However, highly distressed non-compulsive users experienced significant emotional distress related to their pornography use, despite lower usage levels (Vaillancourt-Morel et al., 2017).

These results appear to align with those produced by Bőthe et al. (2020), who performed latent profile analyses on three nonclinical samples recruited from a pornography website and other general sites, using a ten-point scale to measure past-year frequency of use (1 = ‘never’, 10 = ‘6 or 7 times a week’). They also found that three distinct pornography-use profiles emerged (although the cutoff for a ‘high’ frequency of use is not defined): non-problematic low-frequency pornography use (68-73% of individuals); non-problematic high-frequency pornography use (19-29% of individuals); and problematic high-frequency pornography use (3-8% of individuals) (Bőthe, Tóth-Király, Potenza, et al., 2020). Differences were observed between the problematic and non-problematic high-frequency-use groups: namely, levels of hypersexuality, depression, boredom, susceptibility, self-esteem, moral incongruence, and psychological needs (Bőthe, Tóth-Király, Potenza, et al., 2020). However, in a subsequent study, both frequency and moral incongruence were shown to be among the most robust predictors of PPU (Bőthe, Vaillancourt-Morel, et al., 2024). In summary, while frequency of use may be associated with PPU, it appears that one’s level of moral incongruence in relation to pornography use may be a key factor that activates feelings of guilt, shame, anxiety, depression, and withdrawal symptoms (Bőthe, Tóth-Király, Potenza, et al., 2020; Bőthe, Vaillancourt-Morel, et al., 2024; Roza et al., 2023).

**Therapeutic Options for PPU**

With so many competing models for understanding PPU, it is challenging to develop a scientifically validated treatment approach that effectively addresses the condition and its underlying mechanisms. Treatments based on an incorrect or incomplete model of PPU are not only likely to be insufficient but may even cause harm by exacerbating the problem or neglecting key underlying issues, thus leading to worsened mental health. This problem is compounded by the low number of therapists with adequate training, confidence, and value-alignment to treat PPU (Short et al., 2016), leaving many individuals without access to appropriate care. One study found that 58.9% of 183 surveyed mental health professionals reported not feeling confident in their ability to manage PPU (Short et al., 2016). Another study found that 77.9% of psychotherapists reported receiving little or no information on pornography in graduate training and that therapists' attitudes on pornography led to significant biases in treatment approaches (Ayres & Haddock, 2009). Coupled to this, many patients experience shame when talking about their sexual problems (Bőthe, Baumgartner, Schaub, et al., 2020). As such, people seeking help with PPU may prefer to use self-help resources and technological interventions rather than trying to find a therapist with suitable expertise (Bőthe, Baumgartner, Schaub, et al., 2020). Indeed, results from the International Sex Survey found that while 4%-10% of participants at risk of experiencing PPU had ever sought treatment, an additional 21%-37% wanted to seek treatment, but chose not to due to reasons such as stigma and unaffordability (Bőthe, Nagy, et al., 2024).

Since other disorder classes, such as 'obsessive compulsive disorder' and 'substance use disorder' have been proposed for categorizing PPU (Twohig et al., 2009), there is ongoing debate about whether psychological or pharmacological treatments are most effective. This uncertainty regarding the underlying causal mechanisms of PPU make it difficult to determine which treatment approach – targeting behavioural patterns, targeting neurochemical imbalances, or both – will yield the best outcomes. There is limited evidence for pharmacological treatments for PPU, although naltrexone, a drug typically used for treating alcohol, has shown some potential for suppressing some of the reinforcing properties of PPU (Camacho et al., 2018; Ravish et al., 2024). It is hypothesised that naltrexone works by inhibiting dopaminergic neurons in the ventral tegmental area, a pathway typically utilised by opioids (Borgogna et al., 2023; Bostwick & Bucci, 2008; Camacho et al., 2018; Ravish et al., 2024). There is also much promising research on the effectiveness of certain behavioural interventions for PPU, including cognitive behavioural therapy, acceptance and commitment therapy, and meditation (Crosby & Twohig, 2016; Lotfi et al., 2021; Minarcik, 2016; Pareek et al., 2023; Sniewski et al., 2022; Twohig & Crosby, 2010). Additionally, twelve-step programs for sex, love and pornography addiction are commonly used by individuals, including Sex Addicts Anonymous (SAA) and Sex and Love Addictions Anonymous (SLAA) (C. Andersson et al., 2024; Fernandez et al., 2021a), but there is little research evaluating their effectiveness in PPU treatment. There are concerns regarding the application of an addiction treatment to PPU which, as a manifestation of CSBD, is currently understood to be an impulse-control disorder in the ICD-11, although this classification remains under debate (C. Andersson et al., 2024; Kraus et al., 2018).

Furthermore, there are several online self-guided interventions, including the subreddit r/NoFap on the website reddit.com and on the website nofap.com (*NoFap® Porn Addiction Recovery*, 2022), which encourages participants to take part in a 'Reboot' in which they abstain from pornography use for 90 days (Burnett, 2022; Chasioti & Binnie, 2021). Overall, the quality of evidence for these treatment methods remains low (Roza et al., 2023), but there is growing evidence that abstaining from pornography often leads to positive mental health effects, along with some possible withdrawal symptoms (Fernandez et al., 2020). Straub and Schmidt (2022) found that participants who abstained from pornography and masturbation for three weeks experienced strongly reduced mental and physiological fatigue, as well as moderately increased wakefulness, activity, inspiration, self-control, and reduced shyness compared to a control group, although both groups were voluntary. Lewczuk et al. (2022) demonstrated that people with PPU experience a range of withdrawal symptoms in the short-term, including frequent sexual thoughts that are difficult to stop, increased arousal and sexual desire, irritability, mood changes, increased stress, sleeping problems and restlessness, problems with concentration, depressive mood, and guilt. However, there are also potential benefits in the long-term. A qualitative analysis of the r/pornfree subreddit found that abstinence from pornography was often linked with perceived positive outcomes (Jenkins, 2018). Furthermore, Lambert et al. (2012) found that participants who abstained from pornography for three weeks experienced increased commitment to their romantic partners compared to participants who abstained from eating their favourite food during the same period. However, it is possible that some of these positive effects stem from the sense of virtue attained from abstinence, or from group dynamics such as social reinforcement. Hence, further research is needed in this area to determine if there are potential benefits to online interventions such as the r/NoFap subreddit, and if so, to understand the underlying factors driving these effects.

**Technological Interventions for PPU**

Another form of intervention is that provided via mobile application, also known as an mHealth intervention. The introduction of smartphones into modern society provides an unprecedented opportunity to deliver mobile therapies to people globally. Having a mobile app that can anonymously guide the user through the steps required to manage PPU or regulate Internet content could be valuable to people who feel uncomfortable disclosing their struggles to others (Silva et al., 2015). If the research suggesting that PPU can lead to negative mental health outcomes is valid, then the learnings from mHealth technologies in other fields may be useful for developing apps that can help people struggling with PPU. Unlike traditional therapy, these apps are often free and immediately available, thus supporting participant autonomy, expanding access, and reducing access stigma (Bőthe, Baumgartner, Schaub, et al., 2020).

There are several examples of interventions delivered via mobile app that have proved effective in improving health behaviours and psychological and physical symptoms (Heron & Smyth, 2010). There is also growing evidence that such technologies can be beneficial for people with mild to moderate levels of depression or anxiety (G. Andersson et al., 2005; Andrews et al., 2010; Mohr et al., 2013; Richards & Richardson, 2012; Shen et al., 2015; Spek et al., 2007; Watts et al., 2013). For example, one meta-analysis of 22 studies found that computerised cognitive behavioural therapy via the Internet can provide effective health care for people with anxiety and depressive disorders, particularly if they might otherwise remain untreated (Andrews et al., 2010).

However, there are possible harms associated with using unregulated applications for PPU treatment. For example, an analysis of peer support social network services for people with depressive tendencies highlighted several potential harms of using such tools, including contagion of stress and other emotions from peer to peer, and the possibility of receiving egocentric comments from other users that may hinder one's recovery (Takahashi et al., 2009). Similar concerns have been raised about unregulated online forums such as the r/NoFap platform, which has been criticised over high levels of unscientific information, antisemitism, misogyny, and conspiracy theories (Burnett, 2022; Chasioti & Binnie, 2021; Perry, 2020; Prause, 2017, 2019; Taylor & Jackson, 2018).

There are a number of small-scale studies that have examined the efficacy of short interventions to reduce PPU, although these have mainly focussed on in-person cognitive behavioural therapy and acceptance and commitment therapy, rather than mHealth therapies (Bőthe et al., 2021; Crosby et al., 2011; Heninger, 2016; Minarcik, 2016; Twohig & Crosby, 2010). The 'Hands-off' trial was an example of a large, two-armed randomised controlled trial examining the effectiveness of a six-week online intervention for PPU (Bőthe, Baumgartner, Schaub, et al., 2020; Bőthe et al., 2021). Participants in the intervention arm were required to complete six modules over six weeks, practising techniques such as cognitive behavioural therapy, motivational therapy, and mindfulness. Levels of PPU were measured before and after the intervention, along with participants' frequency and duration of pornography use, while daily measurements of mood were taken throughout the intervention period (Bőthe, Baumgartner, Schaub, et al., 2020; Bőthe et al., 2021). At the six-week follow-up, the intervention group reported significantly lower levels of PPU, frequency of pornography use, self-perceived pornography addiction, and pornography craving, as well as higher pornography avoidance self-efficacy. In contrast, the control group showed no change in usage (Bőthe et al., 2021).

While the 'Hands-off' trial provides promising evidence for the effectiveness of online interventions for PPU, its reliance on self-reported data introduces a potential bias, particularly if participants are not reporting their pornography use accurately. Moreover, the study experienced substantial attrition in the intervention group using EMA methods, with only 13 of 123 participants (10.6%) completing the study, compared to 78 of 141 participants (55.3%) in the control group with no EMA methods. Additionally, the focus on short-term outcomes leaves questions about maintenance effects, highlighting the need for extended follow-up studies to assess lasting behavioural change. However, there are other studies underway, such as the PornLoS Treatment Program study, which is examining a psychotherapeutic approach to PPU treatment, and will test two variants of the program that differ in treatment goals – one being abstinence, and the other being reduced pornography use (Stark et al., 2024). The PornLoS study will also include a mobile app as part of the treatment program (Stark et al., 2024). It is hoped that studies like these can inspire further research in this field, leading to improved mobile therapies for people struggling with PPU.

**Summary**

This literature review demonstrates that there are clear links between PPU and negative mental health and social outcomes, with moral incongruence appearing to play a moderating role in these relationships. However, the causal mechanisms underlying these relationships remain poorly understood. There is much debate on whether PPU should be classified as an impulse-control disorder, an obsessive-compulsive disorder, or an addiction, partly due to a lack of knowledge about the symptoms produced by pornography use and by abstinence.

Partly due to these uncertainties, the number of scientifically backed therapeutic options for PPU sufferers remains low, especially within the mobile app space. In Chapter 3, I examine the mobile apps currently available to PPU sufferers on the major mobile app stores, to identify the main features that are popular with users, in the hopes that this may guide future research into the effectiveness of these features in managing PPU.

In turn, Chapter 4 provides an overview of the modelling techniques and methods used in the remainder of this thesis, focusing on the psychophysiology of addictive and compulsive behaviours. It also covers pharmacokinetic/pharmacodynamic modelling and longitudinal methods like EMA that may improve our understanding of the temporal dynamics of PPU. Thus, Chapters 3 and 4 provide a contextual and methodological foundation for the remainder of this thesis.

# Chapter 3: Content Analysis Study

## Prelude

When I originally created the Harden app, I performed a cursory evaluation of apps currently available for treating pornography addiction on the Android and iOS mobile app stores, and in the process, found several publicly available apps for this purpose. However, when performing the literature review for this thesis, I realised that nobody had conducted a full content analysis of the major app stores to identify apps with other valuable features. Furthermore, there remains virtually no literature assessing the effectiveness of these mHealth apps for managing PPU (Aboujaoude, 2019). This finding is consistent with the lack of literature on many other categories of mHealth apps, such as those for non-medical cannabis use, mindfulness, and Post-Traumatic Stress Disorder - all of which have a large variety of apps available in both Google's and Apple's app ecosystems (Plaza et al., 2013; Rodriguez-Paras et al., 2017; Sedrati et al., 2022). For example, Colbert et al. (2020) reviewed studies of 19 mobile apps designed to manage alcohol consumption, and found that of these apps, only 8 were available in public app stores, with only half of those apps having been scientifically validated to help with reducing alcohol consumption. A similar problem has been observed in related fields (Staiger et al., 2020), making it impossible to know whether people are receiving the most effective interventions available. This highlights the urgent need to assess what mobile technologies are currently being used for managing PPU, particularly as the rate of pornography consumption on smartphones increases (*The 2021 Year in Review – Pornhub Insights*, 2021).

It is possible that several apps claiming to reduce PPU have little to no effect on reducing PPU at best, and at worst may even increase the user's reliance on their device and its associated behaviours (including PPU). As such, there is a need to analyse these apps to identify popular features, assess their quality, and determine if they are supported by scientific evidence. This will help guide the direction of future research, such that a focus is placed on developing apps with efficacious features. In the meantime, it is important that we understand what options are available to people who struggle with PPU in the current market.

At the time of writing this article, there were no apps in either of the Android and iOS mobile app stores that even mentioned the phrase 'problematic pornography use' in their descriptions. A quick review of the app stores suggested that 'pornography addiction' was the most recognised term for PPU, leading me to adopt it as my primary search term. This underscores the ongoing lack of scientific validation in this field and emphasises the urgent need for PPU research to be translated into practical applications for real-world users.

***Manuscript***

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**mHealth Technologies for Managing Problematic Pornography Use: Content Analysis**

***Abstract***

Several mobile apps are currently available that purportedly help with managing 'pornography addiction'. However, the utility of these apps is unclear, given the lack of literature on the effectiveness of mobile health solutions for problematic pornography use. Little is also known about the content, structure, and features of these apps. Hence, this study aimed to characterise the purpose, content, and popularity of mobile apps that claim to manage pornography addiction.

The phrase 'pornography addiction' was entered as a search term in the app stores of the two major mobile phone platforms (Android and iOS). App features were categorised according to a coding scheme that contained 16 categories. Apps were included in the analysis if they were described as helpful for reducing pornography use, and data were extracted from the store descriptions of the apps. Metrics such as number of user ratings, mean rating score, and number of installations were analysed on a per-feature basis.

In total, 170 apps from both app stores met the inclusion criteria. The five most common and popular features, both in terms of number of apps with each feature and minimum possible number of installations, were the ability to track the time since last relapse (apps with feature = 72/170, 42.4%; minimum possible number of installations = 6,388,000), tutorials and coaching (apps with feature = 63/170, 37.1%; minimum possible number of installations = 9,286,505), access to accountability partners or communities (apps with feature=51/170, 30%; minimum possible number of installations = 5,544,500), content blocking or content monitoring (apps with feature = 46/170, 27.1%; minimum possible number of installations = 17,883,000), and a reward system for progress (apps with feature = 34/170, 20%; minimum possible number of installations = 4,425,300). Of these features, content-blocking apps had the highest minimum possible number of installations. Content blocking was also the most detected feature combination in a combinatorial analysis (with 28 apps having only this feature), but it also had the lowest mean consumer satisfaction rating (4.04) and second-lowest median rating (4.00) out of 5 stars. None of the apps reviewed contained references to literature that provided direct evidence for the app's efficacy or safety.

In conclusion, there are several apps with the potential to provide low- or zero-cost real-time interventions for people struggling to manage problematic pornography use. Popular app features include blockers of pornographic content, behaviour monitoring, and tutorials that instruct users how to eliminate pornography use. However, there is currently no empirical evidence to support the effectiveness and safety of these apps. Further research is required to be

able to provide recommendations about which apps (and app features) are safe for public consumption.

### *Introduction*

#### **Background**

Internet pornography use is becoming increasingly normalised worldwide as the rapid proliferation of the Internet and personal computing devices, coupled with widespread cultural acceptance of pornography, has accelerated its spread (Perry, 2018a). An analysis of website traffic in Poland found a 310% increase in the number of people who used pornography on the web between October 2004 (2.76 million) and October 2016 (8.54 million) (Lewczuk, Wójcik, et al., 2022). In 2019 alone, there were over 42 billion visits to Pornhub, the world's most popular pornography website (*The 2019 Year in Review – Pornhub Insights*, 2019). The use of the Internet for sexual pleasure is likely to become more prevalent as people's time spent on the Internet increases (Cooper et al., 1999).

Problematic pornography use (PPU) – defined here as compulsive, dysregulated, or excessive pornography use – is considered a subcategory of Compulsive Sexual Behaviour Disorder (CSBD) in the ICD-11. However, there remains controversy over whether 'pornography addiction' in the classical sense of an addiction exists, with opponents of this construct suggesting that compulsive pornography use is a coping mechanism for issues such as depression and anxiety. Still, there remains a high prevalence of anecdotal evidence for self-perceived pornography addiction in popular culture and web-based discourse, with many believing that pornography use can cause both depression and anxiety, among other disorders (Chasioti & Binnie, 2021).

#### **Technological Interventions for PPU**

The introduction of smartphones into modern society provides an unprecedented opportunity to deliver mobile therapies to people on a global scale. A mobile app that can anonymously guide the user through the steps required to manage PPU or regulate Internet content could be valuable to people who are uncomfortable disclosing their struggle with PPU to another person. Such mobile health (mHealth) apps already exist, and unlike traditional therapy, these apps are often free and immediately available, thus supporting user autonomy and expanding access. However, it should be noted that such interventions are often hindered by low treatment commitment and adherence, limited flexibility and tailoring, and higher dropout rates than in-person therapies (Haug et al., 2018; Schaub et al., 2016).

One of the difficulties of delivering interventions for reducing pornography use online is the fact that pornography is delivered over the same medium. In a qualitative review of abstinence journals on a web-based ‘rebooting’ forum for PPU, Fernandez et al. (Fernandez et al., 2021b, p. 719) found that many of the forum’s members struggled with “the seeming inescapability of cues” that triggered pornography cravings, particularly on electronic media such as the Internet or television. Moreover, these cues often appear unpredictably, making casual Internet browsing a risky behaviour for those attempting to reduce PPU (Cooper, 1998; Cooper et al., 1999; Fernandez et al., 2021b; Mihajlov & Vejmelka, 2017; Wolak et al., 2007). Before Internet pornography was introduced, one simply had to distance oneself from physical sources of pornography, such as magazines (Regan, 2021). Today, distancing is harder to achieve, given the amount of time we are connected to the Internet and the ready accessibility of web-based pornography through our devices.

### Currently Available mHealth Therapies

Despite the popularity and potential of mHealth apps for managing PPU (Aboujaoude, 2019), there remains practically no literature assessing their effectiveness. This is consistent with the lack of literature on many other categories of mHealth apps, such as those for nonmedical cannabis use, mindfulness, and posttraumatic stress disorder, all of which have a large variety of apps available in both Google’s and Apple’s app ecosystems (Plaza et al., 2013; Rodriguez-Paras et al., 2017; Sedrati et al., 2022). This is concerning because it makes it difficult to determine whether people are receiving evidence-based or effective interventions. Colbert et al. (2020) reviewed studies of 19 mobile apps designed to manage alcohol consumption; of these apps, only 8 were available in public app stores, and only 4 of these 8 apps had been demonstrated to help reduce alcohol consumption in the literature. A similarly low conversion rate has been observed in related fields (Staiger et al., 2020).

One example of a therapeutic technique for PPU management is an app that can block pornographic websites, which hypothetically increases the number of barriers to accessing pornography, giving the user time to resist their urges better. However, these apps can often be turned off or bypassed and may not block the entire spectrum of sexual content, such as audio or text. Progress has been made on the use of machine learning models to detect pornographic imagery automatically, and these models may be incorporated into this kind of software in future (Perez et al., 2017). However, these systems need to be used with care because the potential for false positives is high, leading to censorship of harmless content such as tutorials on sexual health (Richardson et al., 2002), which could ultimately be harmful. Such a filter must be sensitive enough to capture a substantively high percentage of pornographic material but not so sensitive that it makes Internet browsing a frustrating experience because of too many false positives, which can cause users to uninstall the program; for instance, biasing the software toward a skin-based detection method can lead to false positives in many domains (such as swimming, wrestling, or underwear modelling) and false negatives for sexual content of a nonnude nature (Perez et al., 2017). This classification problem will also require constant updating as new sexual content and imagery forms are produced. In addition, these classifiers often do not recognise alternative media such as erotic literature or audio, although recent advancements in artificial intelligence algorithms may change this in future (Dell'Acqua et al., 2023).

Browser extensions that provide broad-spectrum content blocking, such as uBlock Origin (*uBlock Origin - Free, Open-Source Ad Content Blocker.*, 2022) and BlockSite (*BlockSite*, 2022), can also be configured to block pornography. Many of these digital self-control toolsare free (or have a free tier) and are thus available and effective for a broad consumer base (Gardner, 2011). These tools are also examples of a just-in-time adaptive intervention, where the intervention is delivered when the user needs it most – as they are beginning down the path toward relapse by browsing a website that they know to be tempting (Nahum-Shani et al., 2018). An example of a scientifically grounded just-in-time adaptive intervention is the Addiction–Comprehensive Health Enhancement Support System (A-CHESS), a smartphone app designed to improve continuing care for alcohol use disorders (Gustafson et al., 2014). However, there seems to be no evidence-based version of this for PPU.

**Interventional Studies**

Content-blocking apps are just one example of a wide variety of tools available to help people with PPU. However, very little research has examined the effectiveness of any of these tools. Although some studies have examined the efficacy of short interventions to reduce PPU, these have generally been small scale and focused on in-person cognitive behavioural therapy and acceptance and commitment therapy, rather than mHealth (Bőthe et al., 2021; Crosby et al., 2011; Minarcik, 2016; Twohig & Crosby, 2010). At the time of writing, only one large-scale study has investigated the effectiveness of a web-based intervention for people struggling with PPU (Bőthe et al., 2021). The Hands-off trial, currently ongoing, is a 2-armed randomised controlled trial examining the effectiveness of a 6-week web-based PPU intervention (Bőthe, Baumgartner, Schaub, et al., 2020; Bőthe et al., 2021). The intervention arm draws from techniques such as motivational therapy, cognitive behavioural therapy, and mindfulness to provide 6 modules to the participant over 6 weeks, with baseline and follow-up surveys used to measure self-reported scores on the Problematic Pornography Consumption Scale, along with other measurements such as frequency and duration of pornography use as well as mood tracking (Bőthe, Baumgartner, Schaub, et al., 2020; Bőthe et al., 2021). Preliminary analysis shows that participants in the intervention group reported lower levels of PPU use, including frequency of use, whereas the control group showed no change in use (Bőthe et al., 2021). However, the Hands-off intervention only assesses the effectiveness of a subset of potential features for PPU interventions and thus can only enhance the credibility of a few apps with comparable features. Furthermore, no research exists that can provide an overview of the techniques that are currently being used by consumers for PPU management.

Thus, this research aimed to categorise the features of currently available smartphone apps for managing PPU to obtain an overview of the techniques that are most prevalent and in demand. This will help to direct future research in this area and create potential therapies that can use the combined strengths of in-demand features that have been scientifically validated.

### *Methods*

#### Feature Analysis

I performed a restricted systematic feature analysis of mobile apps available on the two leading mobile app stores: Google Play Store (Android) and Apple App Store (iOS). Apps available on either mobile phones or tablets were included in the review. The review methodology was based loosely on that used in the study by Shen et al. (Shen et al., 2015), but this is not an exhaustive systematic review of all software; rather, it is an assessment of what is currently available in the mobile app space only.

On February 3, 2022, the key phrase 'pornography addiction' was entered into the search bar of the two main mobile app stores. The results were categorised by a member of the authorship team (NH) according to a coding scheme that was iteratively updated throughout the categorization process (Textbox 1). This process was performed under the supervision of the other members of the authorship team (LD, MW, and MP). Modifications to the procedure were made when unique, non-classifiable features were observed, in which case an adjacent category was expanded to include the feature, or a new category was created. The final coding scheme contained 16 app feature categories (Textbox 1).

Textbox 1: Final coding scheme used to categorise app features.

Feature name and type of feature

- Track: variable tracking
- Stats: statistical insights derived from variable trackers or streak trackers
- Tutor: tutorials or coaching sessions, often delivered in written, audio, or video format

- Exercise: exercises or meditations, often in the form of cognitive behavioural therapy, motivational therapy, or hypnosis
- Block: content blocking or monitoring
- Streak: tracking of streak length (the time since the last relapse), often called a day counter, streak timer, or progress tracker
- Account: accountability partner or access to a community forum
- Diary: diary or journal with the ability to take notes or set reminders
- Badge: badges, often as rewards for reaching a new streak length
- Distract: distractions for users with high urge levels, often in the form of games, soothing music, or relaxing scenery
- Quote: motivational quotes, often from famous and historical figures
- Finance: financial tracker providing an indication of money saved via abstention from pornography use
- Locate: location tracker
- Panic: panic button, often sending the user to a site with motivational quotes, encouraging videos, or blog posts
- Religion: an explicitly religious element that is conservatively opposed to pornography use
- Test: a survey that screens for pornography addiction

### Inclusion and Exclusion Criteria

Apps were screened and included in the study based on the app's description, title, and screenshots. Only apps described as helpful for reducing pornography use were included in the review, and this included apps that had a broader focus but still mentioned pornography. For example, an app designed to target Internet addiction, gaming addiction, and pornography addiction would have been included. Apps were excluded if they did not provide sufficient information to classify the app's functions, offered pornographic content or did not claim to help participants to reduce or manage pornography use. Apps that were apparent duplicates of higher ranked apps as determined by their near-identical descriptions or user interfaces were recorded and excluded from further analysis.

The following information was extracted from the store descriptions of the apps: app name, creator, number of user ratings, mean rating score, and number of installations (Android only). There were several notable differences between the available information in Apple's App Store and the Google Play Store (Textbox 2), making it challenging to aggregate statistics between the two stores.

Textbox 2: The differences between the available information in Apple's App Store and the Google Play Store.

Notable differences between the App Store and Google Play Store with regard to app information

- The number of app installations was only provided in the Google Play Store.
- The number and value of ratings were only recorded for the most recent version of iOS apps, whereas they were recorded for all historical versions of Android apps. This reduced the number of ratings available for iOS apps but also introduced a potential bias toward previous versions of Android apps that did not contain newer features.
- Although some apps were identical between the stores, their creator was listed under a different name for each store. Hence, best judgment had to be used to categorise identical apps between the stores.
- The Apple App Store provides specific details about in-app purchases, whereas the Google Play Store offers a range of potential in-app costs. However, the variety of pricing models for each app made the cost of apps a difficult metric to assess objectively; hence, this was excluded from the analysis.

***Results***

**General Characteristics**

The data set for the content analysis can be found in the online Appendices (N. Henry, 2024a). The search yielded 286 apps across both platforms, of which 17 (5.9%) apps had descriptions in languages other than English and were excluded from further analysis. Of the remaining 269 apps, 93 (34.6%) were excluded because they did not aim to manage pornography use, whereas 6 (2.2%) were excluded because they were duplicating an app higher in the search rankings. This left 170 relevant English-language apps to analyse, of which 121 (71.2%) were for Android devices only, and 29 (17.1%) were for iOS devices only, whereas 20 (11.8%) apps were found on both platforms (Figure 1).

Only the Google Play Store (Android) reported the number of app installations and only in predefined ranges. The most frequent range of installations for Android apps was 10,000 to 50,000, achieved by 25.6% (31/121) of the apps, whereas 2.5% (3/121) of the apps were installed in the range of 5 million to 10 million, the highest recorded range.

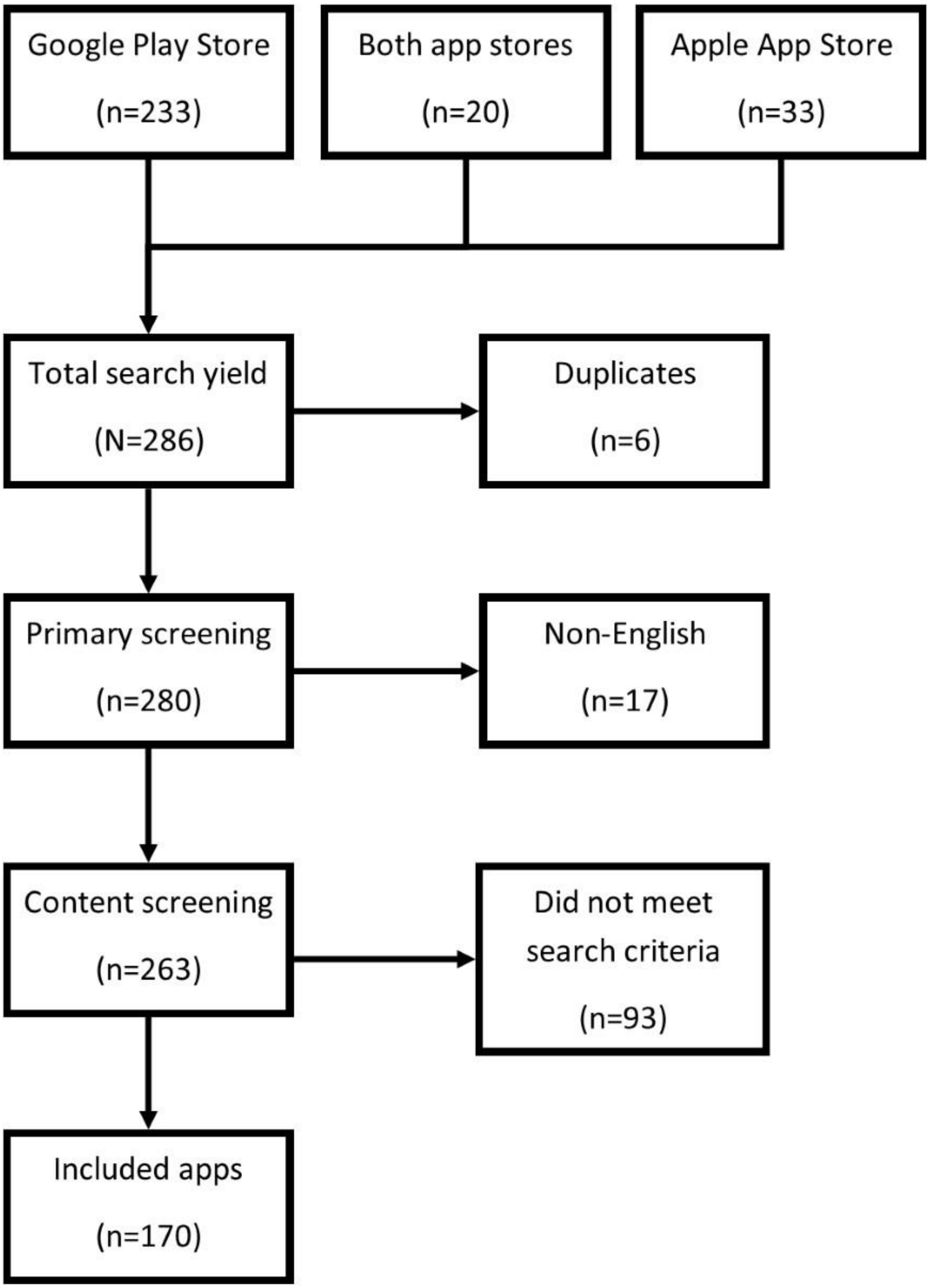


*Figure 1: Flow diagram illustrating exclusion of apps at various stages of the study.*

**Breakdown by Feature**

The number of apps with each feature from both stores was tallied (Figure 2). The *streak* feature, which tracks the time since the last relapse, was the most common in terms of app numbers, with 42.4% (72/170) of the apps providing this feature. The *tutor* feature, providing tutorials and coaching for users, was the second most common feature, offered by 37.1% (63/170) of the apps.

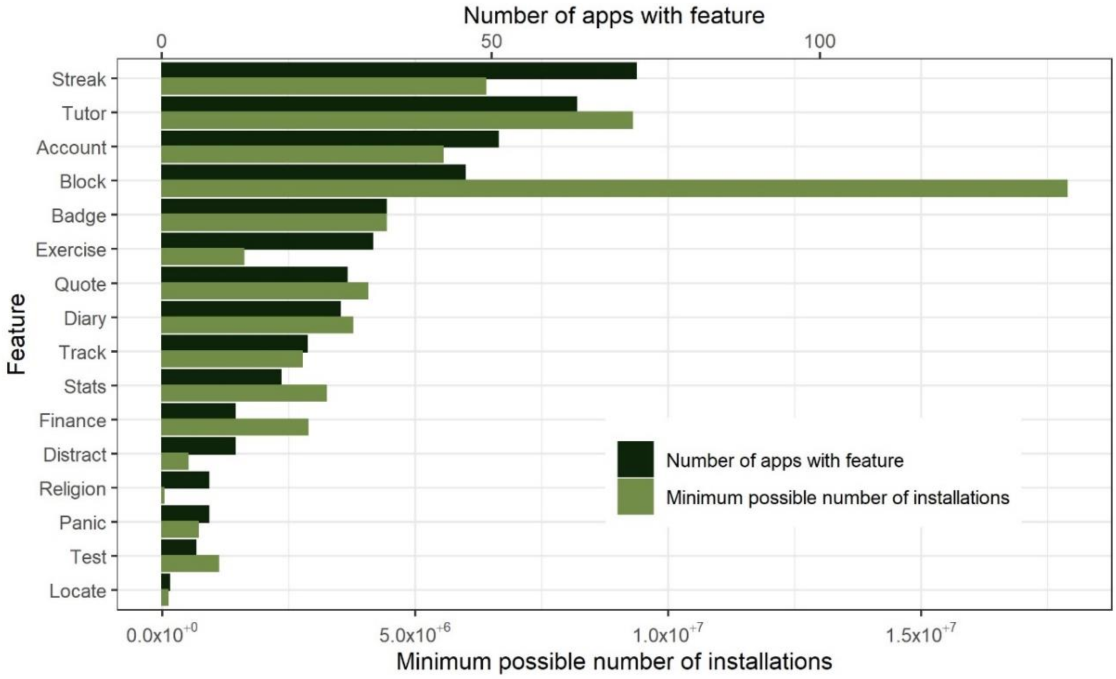


*Figure 2: Number of apps containing each feature for both Android and iOS, and minimum possible number of installations for each feature (Android only).*

In addition, it was possible to calculate the minimum possible number of installations for the Android apps with each feature by summing the minimum value in the range of installations for each app containing the feature (Figure 2). The four most common features in terms of app number (*streak*, *tutor*, *account*, and *block*) were also the four most popular features in terms of downloads, although their rank changed slightly. Notably, the *block* feature, which provided content blocking and monitoring, was only included as a feature on 27.1% (46/170) of the apps but had the highest minimum number of installations at 17,883,000, almost double that of the next highest-ranked feature (*tutor* with 9,286,505 installations).

A combinatorial analysis was also performed. The frequency of different combinations of features was plotted to determine the most common combinations, both in terms of app frequency and the minimum possible number of installations. The results can be seen in Figure 3 for the 20 most frequent feature combinations. Of note, the two top feature combinations were single features – *block* and *tutor* – both in terms of the number of apps with only these features (28/170, 16.5%, and 18/170, 10.6%, respectively) and in terms of the minimum possible number of installations (16,002,000 and 7,244,205, respectively). The following 3 most popular combinations of features (based on minimum possible number of installations) were all individual apps: BlockerX used the *block*, *account*, *diary,* and *test* features; Quitzilla used the *stats*, *streak*, *diary*, *badge*, *quote*, and *finance* features; and I Am Sober used the *track*, *streak*, *account*, *quote*, and *finance* features.

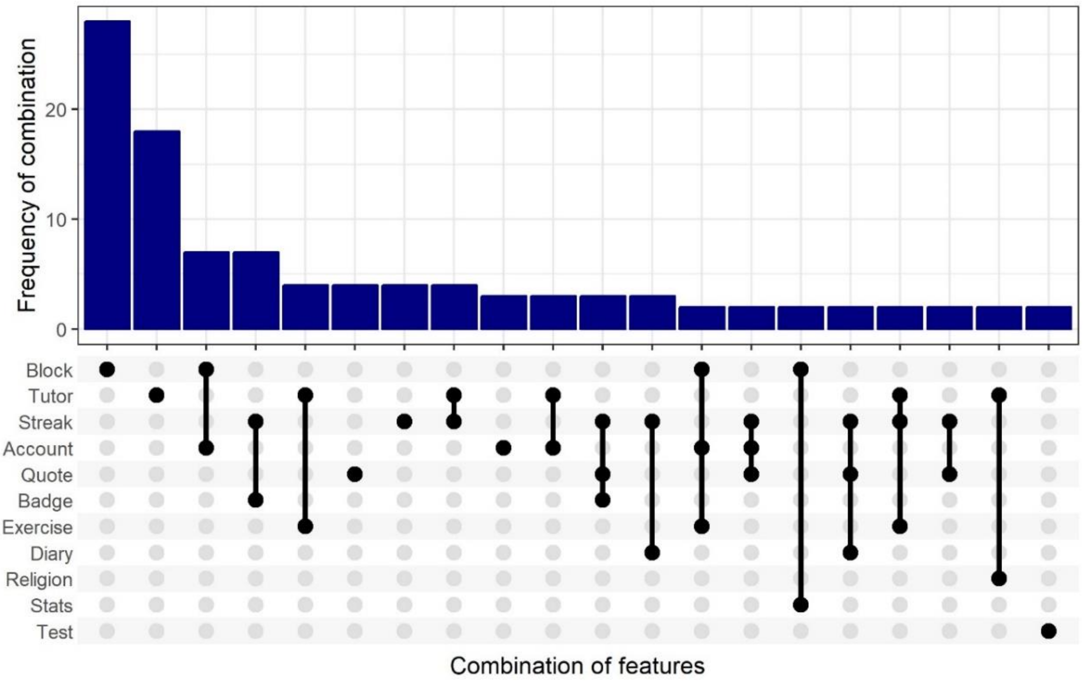


*Figure 3: Combinatorial plot showing the most common combinations of features. Only the top 20 combinations are shown.*

App ratings out of 5 were aggregated between both stores and grouped by feature. The distributions of these ratings are summarised in Figure 4, ordered by mean rating. Only apps that had received at least five ratings were recorded for each feature, and only features with at least five eligible app ratings were plotted. None of the four most common features remained in the top four highest-rated apps by mean or median rating; *streak* came fifth on both counts, with a mean rating of 4.34 and median rating of 4.60. The *quote* and *finance* features, providing motivational quotes and financial tracking, respectively, had the equal highest median rating of 4.70, with *diary*, the journaling feature, having the highest mean rating of 4.69. *Distract*, a feature consisting of distracting activities, had the lowest median rating (4.00). *Block* had the lowest mean rating (4.04) and second-lowest median rating (4.10), despite having the highest minimum possible number of installations. *Tutor* and *account* (a feature providing an accountability partner), both of which scored highly in the minimum possible number of installations and commonality, were either eighth or ninth in the mean and median rating scores (means of 4.24 and 4.21, respectively, and medians of 4.30 and 4.40, respectively). This may indicate that features in higher demand are held to heightened scrutiny or are more challenging to implement at a high standard.

It should be noted that the ratings shown in Figure 4 only consist of apps that received enough ratings to be included in the results. Hence, there may be some bias toward superior-quality apps, as recognised by the market population.

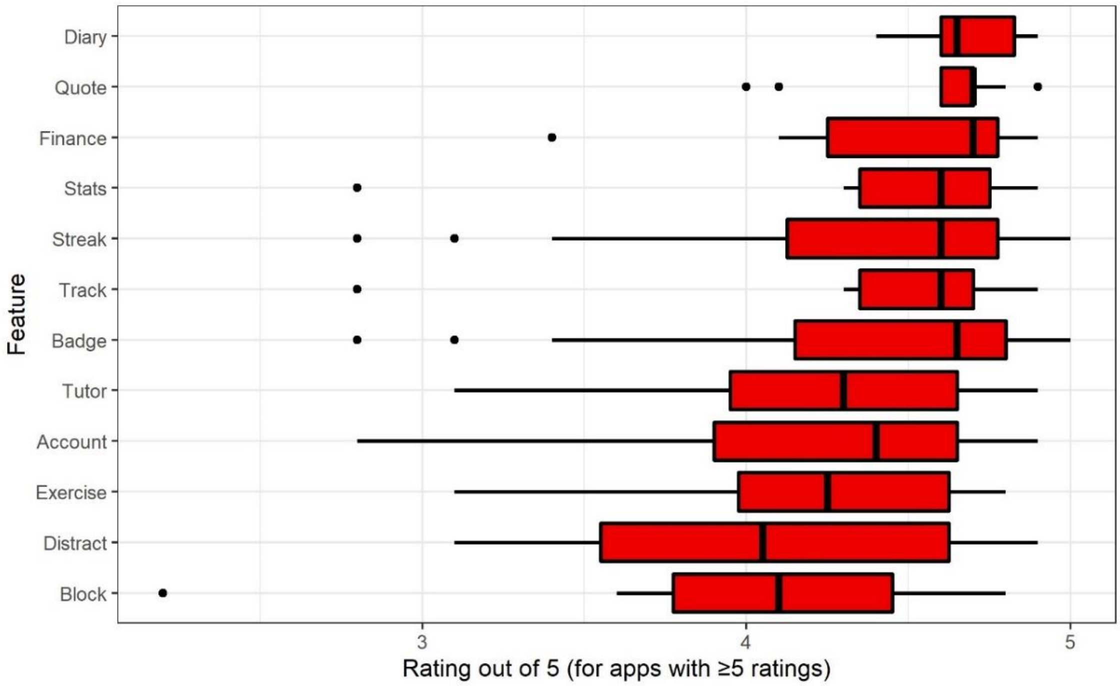


*Figure 4: Distribution of ratings for apps with each feature, for Android and iOS, ordered by mean rating. Only apps that had received at least five ratings were recorded for each feature, and only features with at least five eligible app ratings were plotted.*

### Review of Features Based on Installations

Of the 170 included apps, 46 (27.1%) provided the *block* feature, which provided content blocking or monitoring. Going by the minimum-possible-number-of-installations metric, this feature was the most popular by a large margin (with a score of 16,002,000). Most of this score was due to apps such as BlockSite, which has >5,000,000 downloads on the Google Play Store alone. Of these 46 apps, 15 (32.6%) provided content blocking associated with the *account* feature, usually providing an accountability partner. An example of an app with only these 2 features was Truple, which has been downloaded >100,000 times on the Google Play Store alone. This combination of features was the third most common, with 4.1% (7/170) of the apps having this combination. Still, Truple only came 12th in the ranking of the minimum possible number of installations, with a score of 270,000. However, when combined with other features, the minimum possible number of installations increased to 1,780,000. Most of this score came from the BlockerX app, which has >1,000,000 downloads on the Google Play Store alone.

Of the 170 included apps, 63 (37.1%) provided the *tutor* feature, which offered tutorials or coaching in written, audio, or video format; for example, the Life After Pornography Coach app offers >80 video lessons to aid users in their journey. However, for many apps, tutorials were not necessarily the app's main feature but were offered as part of a complete feature set.

Of the 170 included apps, 32 (18.8%) provided the *exercise* feature, with exercises such as guided meditations or modules for cognitive behavioural therapy and motivational therapy. This feature was often combined with the *tutor* feature; for instance, an audio recording often accompanied guided meditations to direct the user through the meditation. Furthermore, 6.5% (11/170) of the apps provided the *distract* feature, often in the form of games or soothing music for users who were feeling urges.

Of the 170 included apps, 51 (30%) provided access to the *account* feature, either in the form of a web-based forum where users could discuss their PPU with others or the ability to communicate with an accountability partner; for example, users were often redirected to subreddit forums such as r/NoFap (which encourages abstinence from pornography, masturbation, and orgasm for 90 days; the name comes from the slang term 'fap', referring to masturbation) or r/pornfree (which encourages abstinence from pornography-induced masturbation but not masturbation itself).

Of the 170 included apps, 72 (42.4%) provided the *streak* feature, allowing users to track their *streak length*: the time (usually in days) since their most recent lapse. This feature was often paired with the *badge* feature, giving the user extra motivation to reach their next target or badge, and also with the *stats* feature, which provided statistical feedback on the user's streak history and associated metrics.

Of the 170 included apps, 28 (16.5%) provided the *quote* feature in the form of motivational quotes, usually as a secondary feature of a more extensive program. Associated with this, 4% (7/170) of the apps had the *panic* feature, generally in the form of a *panic button*, which the user can press when their urge levels escalate. This typically directed a user to a website with randomised links, often with motivational quotes or a suggestion to perform a quick workout, such as 20 push-ups. An example of this is the panic button created by the r/NoFap subreddit community.

Of the 170 included apps, 27 (15.9%) apps provided the *diary* feature, allowing users to record self-reflective notes on their recovery process. This helps users to identify triggers, relapse pathways, and successful strategies for overcoming pornography use.

Of the 170 included apps, 22 (12.9%) provided the *track* feature, allowing users to record their variables on a daily or instantaneous basis. Of these 22 apps, 10 (45.5%) also provided the *stats* feature, generally as a summary of insights derived from these tracked variables, often in association with the *streak* feature. Of the 170 included apps, 11 (6.5%) also included the *finance* feature, revealing how much money the user was potentially saving by reducing their pornography use.

The three least popular features were *test*, *locate*, and *religion*. Only 2.9% (5/170) of the apps provided any form of survey or test for PPU, whereas 0.6% (1/170) of the apps provided *locate* as a feature. This feature represents a type of relapse prediction service, in that the aim is to learn and highlight locations where the user may be more prone to relapse. Only 4.1% (7/170) of the apps had the *religion* feature, which had the lowest minimum possible number of installations of all features listed, with a score of 21,110. Of these 7 apps, 6 (86%) also provided the *tutor* feature, generally providing helpful scriptures, devotional passages, or prayers.

### *Discussion*

#### Principal Findings

It seems that the academic literature on PPU is divorced from the technological interventions currently available. None of the apps reviewed contained references to literature that provided direct evidence for the app's efficacy or safety. However, several apps reported anecdotal evidence that supported their real-world effectiveness. Furthermore, a lack of scientific studies examining a feature's effectiveness does not necessarily mean that there is no rationale for specific in-app features. The perceived utility of a feature can be partially inferred from its demand in the real world, even if the implementation is imperfect. The relationship between feature utility and real-world demand may be mediated through the number of positive reviews left on apps with the feature, which is indicative of the feature's effectiveness and likely to encourage a higher number of installations for these apps. Still, further research is required to consolidate the evidence base into a whitelist of safe apps for public consumption.

#### Utility of Features

Based on the minimum possible number of installations, content-blocking apps are the most popular on the Google Play Store but have a lower mean rating than apps that do not offer content blocking. The high popularity score suggests that many users attempt to distance themselves from sources of pornography while trying to remain connected to smartphones and the Internet. There is much anecdotal evidence on the Internet supporting these apps, which are also popular in related fields such as Internet addiction. Notably, Lyngs et al. (2019) performed a systematic review of digital self-control tools and found that the most prevalent feature (found in 74% of the tools) involved blocking or removing distractions. Still, despite the robust demand for these apps and their apparent utility, there are no studies investigating the effectiveness of content-blocking apps with regard to PPU reduction. However, the comparatively low mean rating suggests that these apps are not as effective as their users would hope, compared with their expectations for other features.

It is possible that these content-blocking apps may be advertised more than apps with other features, and customers may resent paying for these apps, which are generally more expensive than other apps because of technical requirements such as virtual private network services. By contrast, as discussed earlier, it is challenging to create and maintain a content filter with sufficient sensitivity and specificity to satisfy the market mainly because web-based content keeps evolving. The mismatch between the difficulty of this task and the expected quality of these apps may be more significant than the difficulty-quality mismatch for other features; for instance, an app that provides cognitive behavioural therapy tutorials may only need to provide minimal benefit for its users to rate it highly because the user will not blame the app for causing a relapse. However, if a content-blocking app fails to block a new pornographic site, which leads to a user relapsing, this will likely lead to a negative review. This may explain why the *block* feature scored very highly in terms of the minimum possible number of installations but had a relatively low median rating compared with other features.

An interesting alternative to counteract this weakness is Truple, an app that takes screenshots of all browsing behaviour, analyses them, and flags potential sexual content to an accountability partner (*Truple - Defeat Porn & Online Filth with Screenshot Accountability*, 2022). In theory, this reduces the temptation to uninstall or bypass the app, which is a problem for some apps with the *block* feature. However, as is the case with using a therapist, not all users are willing to share their private browsing information with even trusted friends, which may reduce use of this feature. In addition, the app does not prevent users from viewing the websites, which indicates that it may be fortified by the addition of the *block* and *quote* features. Motivational quotes have some potential to provide positive boosts to self-esteem and self-efficacy for patients using mHealth interventions to recover from PPU (Bedrov & Bulaj, 2018). The addition of motivational quotes may provide timely reminders to stay away from distracting material that has the potential to devolve into PPU.

Badges seem to have potential as a means of gamifying the recovery process and generating positive reinforcement (Rajani et al., 2021) and have been shown to improve motivation in therapeutically administered tasks (Cheng et al., 2019). However, the use of progress trackers is controversial. Despite being popular, it is plausible they can be detrimental to users who relapse because they may induce additional feelings of guilt and anxiety upon breaking a streak, perpetuating the feelings that led to a relapse in the first place (Shen et al., 2015). Still, these feelings may be a necessary part of the recovery process. Using the prospect theory framework developed by Kahneman and Tversky (Kahneman & Tversky, 2018), one can define the risk of experiencing post-relapse depression as a potential loss, which the user must compare with the momentary pleasure of relapse as a gain. In this framework, healthy use of the *streak* feature creates a positive feedback loop, whereby the user experiences increasing loss aversion as their streak length increases, and memories of past failures inspire greater motivation to reduce future losses. However, an alternative positive feedback loop is also possible, where the feelings of guilt and depression brought about by relapse cause the user to turn to pornography to avoid these feelings (Grubbs, Stauner, et al., 2015). These questions invite further research to determine whether the utility of this feature varies within a population of participants struggling with PPU.

In many ways, apps combining the *track* and *stats* features act as a self-monitored Ecological Momentary Assessment, where the user both records and analyses their data (Shiffman et al., 2008). Such an app's effectiveness will be inherently limited by the ability of its users to interpret such data accurately, particularly those users without a sufficient level of scientific training. Hence, app creators must balance the complexity of the statistical analysis they provide against the ability of their users to interpret these data meaningfully.

The Fortify app (as part of Impact Suite) allows users to track their variables over time, including urges and variables related to wellbeing. It then performs analytics on these variables over time, allowing users to self-examine their weaknesses. The app also includes a personal journal, training and meditation sessions, community forums, and accountability partners. This is the only mobile app I found with a comparable alternative in the literature, although that trial (the Hands-off study) is not yet complete and focuses more on providing coaching modules and exercises for users (Bőthe, Baumgartner, Schaub, et al., 2020). However, it has shown promising results so far, with indications that the combination of variable tracking with modules and community messaging are an effective way to manage PPU (Bőthe et al., 2021).

Although several apps provide the ability to record one's urges at the end of each day, I found no app that allows the user to record their urges instantaneously, with associated follow-up recommendations such as taking a break from the Internet or performing exercise. If a user performs urge tracking at regular intervals, they can monitor responses to various stimuli in real time and adjust their behaviours when urge levels increase; for example, a user may find that their urges increase rapidly while browsing a particular website and choose to regulate their exposure to this website. In addition, once they have been tracking their urges for a while, the user may become more attuned to scenarios that increase their urges and formulate strategies to escape these scenarios. This could take the form of a self-regulated just-in-time adaptive intervention, where the user records their urge levels and responds to the app's subsequent prompt to change their environment, perform exercise, or meditate.

### Motivational Readiness

Despite their lack of grounding in the literature, many of the apps in this analysis seem to have features that align with addiction-management frameworks such as self-regulation theory (Mithaug, 1993) and self-efficacy theory (Maddux, 1995). However, one theory allows us to quantify the effectiveness of the features seen in this review: the dual-threshold model of motivational readiness developed by Kruglanski (Kruglanski, 2017; Kruglanski et al., 2014). In this theory, the degree to which a person pursues a goal state (such as gratification of pornographic urges) is a function of both their motivational readiness to achieve the state and their belief that the state can be achieved (expectancy) (Kruglanski et al., 2014). To put this in the context of PPU, if the user believes that they can access pornography (expectancy), and their desire for pornography is stronger than their will to reduce PPU (motivational readiness), then they will take steps to use pornography in proportion to their desire to use it. However, if they do not believe that they can access pornography, then they will not attempt to use pornography, irrespective of their desire to do so.

Based on this model, one could propose two potential strategies to reduce PPU: either raise the person's motivation to reduce PPU (strategy 1) or increase barriers to pornography access (strategy 2). From a game theory perspective, strategy 2 is superior to strategy 1 because if the user does not meet the requisite threshold for expectancy, they cannot take action to use pornography, regardless of their motivation to do so.

If one tries to categorise the features presented in Textbox 1 based on these strategies, only two features, *block* and *locate*, clearly fall under strategy 1, whereas the other features all fall under strategy 2 (excluding *test*, which is for assessment only). The *locate* feature has a fundamental flaw, in that users regularly spend time in what the feature would consider a high-risk location for pornography use: their own bedroom. Hence, *block* is perhaps the only feature with the potential to eliminate PPU entirely by simply removing the ability to view pornography. Of course, it is virtually impossible to cut off all sources of pornography in the post-Internet age. However, the hypothetical superiority of strategy 2 may explain the popularity of content-blocking apps in this paper's analysis.

### Defence in Depth, or the Swiss Cheese Model

Given that both these strategies have their weaknesses, a potential user may consider combining the strategies to reduce PPU; for example, they may use a *block* app in conjunction with a *track* app to simultaneously monitor their urge levels, place barriers between themselves and exposure, and predict times and environments where they will be at higher risk of relapse. If the *exercise* and *tutor* features with training modules and cognitive behavioural therapy elements are added, the user would have tools available to both increase their motivation and reduce their expectancy.

This combining of techniques is an example of the defence in depth, or Swiss cheese model of risk management, applied to PPU. Defence in depth is a concept created by the National Security Agency to harden computer security. Multiple layers of defence are placed within such a system to provide redundancy of protection if a vulnerability is uncovered (Groat et al., 2012). Applying this model to PPU, one could view pornography as a 'virus' targeted at the brain. If the user has not put up enough layers of security, then the virus will infiltrate the mind and cause a relapse. Using one layer of security such as the *block* feature will provide some protection but leave multiple vulnerabilities open for the virus to penetrate, much like the holes in a slice of Swiss cheese. However, combining multiple layers of security (for instance, adding regular cognitive behavioural therapy to the user's routines) will reduce the probability of relapse even further by removing some of the *holes* left behind by prior layers of security. Having a unique feature combination may also help create a novel market niche, which seems to have been a successful strategy for several apps.

The defence in depth framework may also benefit apps seeking to differentiate themselves in a competitive app market. From the combinatorics analysis performed in this review, it can be deduced that there are two main strategies implemented by the most successful apps in this space: (1) either implement one desirable feature (such as *block*) exceptionally well, or (2) create a niche market by combining a unique set of features. The second strategy, which aligns with the defence in depth framework, has the potential upside of avoiding competition from numerous other apps, which is the challenge facing apps that only use either the *block* feature or the *tutor* feature.

Even when combined, these technologies are likely not entirely sufficient. People who struggle with compulsive behaviours tend to search for new pathways to indulging in their behaviour and may find ways to bypass multiple protective layers, mainly when triggered or under stress (Gardner, 2011). Hence, the defence set up by the user should comprise both static layers that are always present and dynamic layers that are updated regularly to adjust for any blind spots that may appear (Groat et al., 2012). Using this framework, an example of a dynamic layer would be using the *track* feature to identify new triggers, whereas an example of a static layer would be using pornography blocker software on a web browser. Most users trying to overcome PPU will find that complete abstinence is difficult, but by using the defence in depth model, they can treat each relapse as a weakness to be fixed in their quest to eliminate PPU.

In addition, the *track*, *streak*, and *stats* features can guide the user to adjust their strategy when new weaknesses are uncovered through self-analysis of their data. However, not all users will be equipped with the ability to interpret their data accurately. Furthermore, a software-generated interpretation of user data may provide some insights. Still, it will be limited in the amount of nuance it can collect, particularly when the user's data do not match regular trends. This is where a trained therapist would prove to be a significant addition to the defence in depth strategy, in that they could provide insights that both the user and their software tool are unable to uncover. The therapist will also be less vulnerable to self-evaluation bias.

### Weaknesses of mHealth Solutions

The use of apps to counter apps is counterintuitive (Aboujaoude, 2019) but may be necessary for certain users to form new habits. One of the difficulties of providing a technological intervention for PPU is that pornography is delivered on the same technologies; for example, if one uses a mobile app to track one's relapse statistics, one will likely be using the same device one uses to access pornography. This can have both positive and negative consequences. Some app users may be able to use the intervention to develop alternative habits. However, it is possible that for other users, the reverse will happen, where they link the intervention to continued pornography use, making it a double-edged sword. A separate device (such as a pager) is always an option, but these devices generally have limited functionality compared with a smartphone. To increase the reach of an app, highly accessible technologies should be used, which in the case of pornography users is most likely their smartphone (*The 2021 Year in Review – Pornhub Insights*, 2021).

No apps in this review had any screening tools for PPU grounded in the literature. It could be argued that a scientifically validated assessment should be mandatory for any app claiming to help with PPU management. Although there remains controversy around the assessment criteria for PPU (Bőthe, Tóth-Király, Zsila, et al., 2017), the lack of a test implies that the user has a problem by default. It could be argued that a false positive assessment of PPU can induce moral incongruence and subsequent anxiety or depression, potentially leading to a positive feedback loop that increases PPU in some users.

This also highlights that many web-based tools are most effective when guided and recommended by a qualified therapist (Wieczorek et al., 2020). Much work needs to be done to bring the apps reviewed in this study to the therapeutic space, especially considering the lack of therapists trained to treat PPU (Ayres & Haddock, 2009; Short et al., 2016). A therapist may also be able to warn against unintended consequences of certain apps; for example, several apps in this review provided distractions in the form of games or calming music. This feature could be viewed as an alternative to guided meditation, in that it offers a way to direct attention away from pornography. However, many users may also struggle with Internet or gaming addictions, meaning that there is a risk that the user could justify replacing PPU with addictive gaming behaviours. It is possible that the most effective apps for reducing PPU are designed so that the user no longer requires the app once they have achieved their goals and even uses their smartphone less, reducing temptation risk in general. This may be more difficult for apps with the *distract* feature if the app has an addictive design.

### Limitations

The aforementioned quantitative feature analysis focused on mobile apps and excluded other viable software; for example, several browser extensions provide a *block* feature, such as uBlock Origin (*uBlock Origin - Free, Open-Source Ad Content Blocker.*, 2022) or BlockSite (*BlockSite*, 2022), that may not specifically be designed for reducing PPU but can be used to the same effect. One such app, Plucky, blocks all images and videos on the Internet (besides a whitelist of allowed websites) and makes itself inconvenient both to uninstall and to edit the whitelist (*Plucky - a Self-Control Filter*, 2022). The user can customise the app but only after a predefined delay period. In theory, this provides the user with time to overcome their urges and resume baseline behaviour. There are also several apps available on the Internet that provide variations on the accountability feature, including X3Watch (*X3watch - Internet Porn Accountability Software*, 2022) and Qustodio (*Parental Control and Digital Wellbeing Software*, 2022), that were excluded from this review. Many of these apps are designed to broadly reduce Internet use, of which pornography is a use case. Even the r/NoFap subreddit and the associated NoFap website (*NoFap® Porn Addiction Recovery*, 2022) could be considered a technological intervention of sorts, providing the *streak*, *account*, *tutor*, *exercise*, and *panic* features. In summary, there are many self-help resources and associated software-based interventions available on the web, many of which could be used to complement the mobile apps included in this review. More research is needed to evaluate these online alternatives beyond mobile apps.

Any statistical analysis of mobile app stores, including descriptive statistics, is hampered by restrictions on data availability. Both app stores use various methods, including hiding in-app payment and advertising information and using large categories for aggregating and blurring popularity metrics. Variables are not identical between the stores and reflect the preferences of different customer bases; for instance, on average, Apple customers are likely to have greater financial resources than Android customers because Apple mobile phones tend to be more expensive than equivalent Android mobile phones (Sheikh et al., 2013). In addition, it is impossible to deduce how much promotional work has been done behind the scenes to advertise these apps. Hence, the popularity metrics provided here are a poor representation of the actual demand for and quality of features, and should only be interpreted as indicative of potential trends in this space. Non-English-language apps were also excluded, providing another potential source of bias to these results.

Furthermore, any measure of popularity is likely to be biased in cases where apps are used for purposes other than managing PPU; for example, BlockSite, which has at least 5,000,000 downloads on the Google Play Store and contains the *block* feature, is also provided to the user for *blocking distracting websites*, not just pornographic ones (*BlockSite*, 2022). Removing this app and others with multiple purposes may affect the ranking of features in the popularity metrics used for this study.

***Conclusion***

The mobile app space is replete with apps that seem beneficial to users attempting to manage PPU based on their generally high app store ratings, positive reviews, and high number of installations. In particular, content-blocking apps have clear potential for reducing PPU by removing access to pornography on the user's device. However, there remains a substantive lack of evidence in the scientific literature to quantify the effectiveness of such apps. Although each of these apps has its purported benefits, the most effective method for reducing PPU may lie in combining the most robust features in this space, using a defence in depth strategy of risk management. This could be achieved by using multiple apps simultaneously, although this should probably be performed under the guided hand of a trained therapist, if possible. However, such a strategy is inefficient and cumbersome. Further work is required in this space, both to research the effectiveness of these app features and to consolidate the evidence base into a whitelist of safe apps for public consumption.

## Chapter 4: Models and Methodologies for Understanding PPU

One of the findings from the content analysis study in Chapter 3 was the sheer diversity of apps and features available for people to self-regulate their own pornography use. However, this diversity creates a challenge for both clinicians and individuals: how do we decide which apps and features should be recommended to each individual? Furthermore, there are certain apps that provide seemingly effective solutions (such as blocking access to pornographic content), but that in fact may fail to address the underlying psychological factors that are driving PPU. The decision of how to best treat an individual with PPU is contingent on our understanding of what PPU actually is – psychologically and neurohormonally – as well as what constitutes a healthy limit of pornography use for that individual.

Therefore, in order to develop apps that can effectively treat PPU, there is a need for improved psychological models to quantify how (and on what timescales) pornography use affects mental health in different individuals, based on their unique factors. One way to do this is through mathematical modelling of the temporal dynamics associated with pornography use, which has not yet been explored. Creating such models may provide a better understanding of the psychological and neurobiological markers associated with pornography use, which should assist future researchers in categorizing PPU more accurately, either as an impulse-control disorder, an obsessive-compulsive disorder, or an addiction. In the remainder of this thesis, I propose that the temporal dynamics of pornography use may follow an 'opponent process' model. In Chapters 5 and 6, I attempt to simulate, quantify, and validate this model both computationally and with experimental data. The opponent process model is not meant as an alternative to current models, such as the moral incongruence model; rather, it builds upon these models in the hope that future researchers can use this theory to develop better, more adaptive mobile therapies for PPU sufferers.

The remainder of this Chapter provides a broader foundation for the behavioural posology study and the Internet Pornography Use (IPU) study in Chapters 5 and 6, offering both biological and mathematical context for the opponent process model in the behavioural posology study, and additional information on the Ecological Momentary Assessment (EMA) methodologies used in the IPU study.

### Allostasis and Opponent Process Theory

Many behaviours produce 'opponent process' effects within the body. Solomon & Corbit's opponent process theory posits that in humans, a stimulus or behaviour can trigger an 'a-process', the initial euphoric response to a behaviour or substance, followed by a compensatory 'b-process' marked by negative feelings such as depressed mood, cravings and withdrawal

(Solomon & Corbit, 1974). Once the b-process subsides, homeostasis is regained. The pleasurable a-process tends to be a motivating force (Solomon & Corbit, 1974), generally accompanied by the release of dopamine or other neurochemicals (George et al., 2012). However, continued activation of the b-process can lead to hedonic allostasis – a condition in which an individual's hedonic set point (i.e., their baseline mood level) shifts from prior homeostatic levels, resulting in a lowered hedonic state; the person returns to homeostasis only when the b-process is no longer activated (Ahmed & Koob, 2005; Solomon & Corbit, 1974). Therefore, the behaviour acts as a stimulus that, if chronically repeated, causes the individual to feel depressed due to hedonic allostasis and chronic deviation of the brain's basal reward system from its normal set point, as demonstrated in Figure 5.

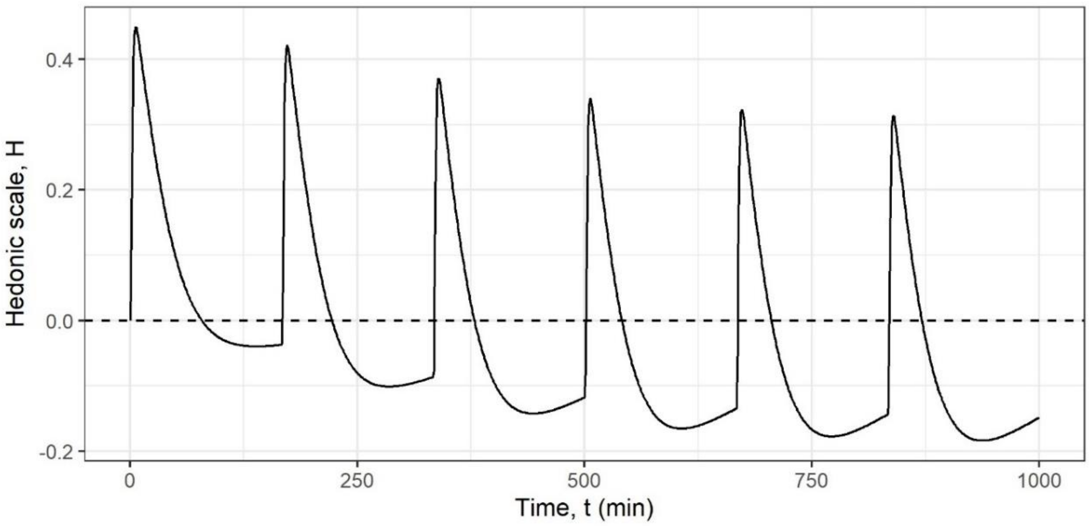


*Figure 5: Simulation of hedonic allostasis (in this case, a decreasing baseline hedonic state – a form of apparent tolerance) produced by repeated opponent processes delivered at a high frequency. The opponent processes in this simulation are defined by a short, intense a-process, followed by a less intense but more prolonged b-process.*

This allostatic deviation is evident in repeated drug use and is characterised by both sensitisation and counteradaptation mechanisms. Sensitisation increases the response to a drug with repeated use, contributing to heightened craving and compulsive drug-seeking behaviour (Robinson & Berridge, 2008). Counteradaptation, on the other hand, involves homeostatic changes that oppose the drug's effects, leading to a buildup of tolerance and dependence on the drug (Cahill et al., 2016; Koob & Le Moal, 2001). This opponent-process theory suggests that the initial positive effects of a drug are countered by negative effects, which become more pronounced with repeated use (Solomon & Corbit, 1974). As the body's homeostatic set point lowers, greater drug intake is required to achieve the same reward, driving further drug use and reinforcing the allostatic state (Koob & Le Moal, 1997). The rate of drug clearance from the body, influenced by pharmacokinetic and pharmacodynamic factors, also plays a role in this process

(Dumas & Pollack, 2008). Ultimately, the allostatic state results in a persistent alteration of the brain's basal reward and stress systems, perpetuating the cycle of addiction.

More generally, allostasis is a process through which the body maintains stability through change, often at a cost, to cope with external and internal stimuli. Unlike homeostasis, which aims to keep conditions constant, allostasis involves a dynamic adjustment process where the body employs a series of recursive compensatory mechanisms to maintain apparent stability (Cannon, 1929; Sterling, 2012). These mechanisms involve both positive and negative reinforcement that can lead to addictive feedback loops. Positive reinforcement increases the likelihood of repeated drug use due to pleasurable effects, such as the euphoria experienced when using substances like cocaine (Koob & Le Moal, 1997). On the other hand, negative reinforcement reduces aversive states, such as the withdrawal symptoms like nausea, pain and anxiety experienced by heroin users (Koob & Le Moal, 1997). When self-regulation fails, emotional distress can increase, leading to repeated relapses and increasing negative affect (Koob & Le Moal, 2001).

The discomfort associated with the reduced state of pleasure produced by hedonic allostasis can act as a behavioural deterrent, effectively serving as a hedonic punishment if the behaviour is repeated too frequently (George et al., 2012). Hence, allostasis can have regulatory effects at the higher levels of cognitive organization (Muntean & Wright, 2007). Thus, it is plausible that allostasis plays a vital role in brain function, enabling us to regulate our internal processes and external behaviours (Katsumi et al., 2022; Sterling, 2012).

The concept of allostasis has many other applications within psychology. For example, it has been proposed that allostasis regulates the detection, processing and reinforcement of social cues, such as the use of oxytocin and other hormones and neurotransmitters to mediate socio-emotional allostasis following traumatic social experiences (Menon & Neumann, 2023). Additionally, there is an allostatic load model of job stress and self-employment stress, even including psychosocial stress among firefighters (Henderson et al., 2023; Igboanugo & Mielke, 2023, 2023; Perrewé & McAllister, 2024). The mechanism for stress-generated opponent processes may be partially mediated by fast (a-process) and delayed (b-process) glucocorticoid feedback (Herman, 2013), among other mechanisms. In many cases, allostatic load can be measured using stress biomarkers (e.g., see Igboanugo & Mielke, 2023; Patel et al., 2019), raising the question of whether it is possible to detect allostasis using other measurement methods, such as by measuring changes in emotional state over time. For example, if repeated pornography use produces allostatic effects, it may be possible to detect this simply by measuring emotional affect in relation to pornography use times using a survey-based method, provided the measurement frequency is sufficient to capture these changes.

## Tolerance

One of the critical components of any addictive feedback loop is the buildup of tolerance – an example of allostatic regulation (Cahill et al., 2016). Tolerance refers to the body's diminished response to a drug following repeated exposure, requiring higher doses to achieve the same effect. However, the body can also develop tolerance to internal neurochemicals like opioids and dopamine (Cahill et al., 2016) in a phenomenon akin to habituation (Peper et al., 1988). Pharmacodynamic tolerance involves changes at the receptor level, such as down-regulation of receptor numbers, reduced receptor density, decreased receptor affinity, or inactivation of the receptor's signalling protein (Y.-W. Li et al., 2003; Williams et al., 2020). This type of tolerance can be distinguished from pharmacokinetic tolerance (which pertains to drug absorption, distribution, metabolism, and excretion) and behavioural tolerance (which involves whole-organism learning processes) (Negus et al., 2010).

Several control theoretic and systems models have been generated to simulate addictive feedback loops, most of them closed-loop models with a form of tolerance feedback loop (Ahmed & Koob, 2005; Amigó et al., 2008; Bobashev et al., 2017; Chou & D'Orsogna, 2022; Dumas & Pollack, 2008; Gårdmark et al., 1999; Levy et al., 2013; Newlin et al., 2012; Peper, 2009; Porchet et al., 1988; Upton & Mould, 2014; Zou et al., 2020). For instance, Peper (2009) simulated a generic tolerance system using two regulators – one fast, to represent the short-term direct effects of the drug, and one slow, to represent the effects of tolerance on the system. Alternatively, Newlin's control theoretic model of opponent processes captures some of the aspects of conditioning, habituation and sensitization (Newlin et al., 2012). However, these models rely heavily on feedback loops with no clear biological justification to produce plausible outcomes; for example, Newlin's model relies on a 'lossy accumulator' to add memory into the system and dynamically adjust the allostatic baseline (Newlin et al., 2012).

Such models tend to be inflexible due to their overreliance on tolerance and feedback or their basis in the neurochemistry of specific drugs (such as nicotine or opioids). Furthermore, in the case of control-theoretic models, certain components do not accurately reflect underlying biochemical mechanisms in a way that can be generalised easily to other biological systems. Moreover, closed-loop models are less tractable than open-loop models that don't require feedback. Yet several of these models still hold utility in modelling real-world addictions. Chou & D'Orsogna's opponent-process model of dopamine concentrations following drug intake produces a realistic version of the opponent-process curve for dopamine (Chou & D'Orsogna, 2022). They note that their model "can be generalised to other forms of chemical or behavioural addictions, such as alcoholism, gambling, or social-media addiction" (Chou & D'Orsogna, 2022, p. 10). Hence, these models may have some heuristic utility in terms of simulating the outcomes and causes of addictive and compulsive behaviours. However, a greater focus on the underlying biological mechanisms behind these behaviours is required if we are to produce more accurate models. This will be particularly critical for models of behavioural addiction and compulsion. For instance, the effects of PPU cannot be attributed to drug consumption and are therefore likely to consist primarily of emotional responses to behavioural events, thus necessitating an entirely different kind of modelling paradigm.

**Dose-Response Relationships**

The dose-response relationship between pornography use and mental health outcomes may take many plausible forms, at both the individual and population levels. One possible model, known as hormesis, describes a biphasic dose-response relationship where low doses of a stimulus produce a positive response from the organism, while higher doses produce a negative response (Agathokleous et al., 2020). Numerous examples of hormesis exist in nature (Schirrmacher, 2021), of which over 5600 peer-reviewed examples can be found in the Hormesis Database (Calabrese & Blain, 2005). Several biological phenomena with biphasic or triphasic dose-response relationships may be described as hormetic phenomena, including the Goldilocks zone (Alleman et al., 2014), the Yerkes-Dodson law in psychology (Calabrese, 2008c), the therapeutic window (Calabrese, 2008b), and U-shaped or J-shaped curves (Calabrese & Blain, 2009). Generally, dose-response curves have been broadly categorised according to three main labels (Prekeges, 2003), shown in Figure 6:

- Linear No Threshold (LNT) – harm increases monotonically with dose.
- Linear With Threshold (LWT) – harm increases monotonically with dose, but only beyond a dose threshold, known alternatively as the No Adverse Effect Level (NOAEL), hormetic limit, or healthy limit.
- Hormesis – low doses are beneficial, but high doses are detrimental.

Psychologically, substances and behaviours often have healthy limits within which low doses can produce positive hedonic outcomes over both short and long timescales, although these boundaries are often unclear, especially when the dose-response relationship is mediated by frequency of use. Possible examples of hormesis have been discovered in humans using recreational drugs including alcohol (Bryazka et al., 2022; Hodgins et al., 1995; Jarosz et al., 2012) and marijuana (Calabrese & Rubio-Casillas, 2018; Childs et al., 2017; Hodges et al., 2020). For example, Hodgins and colleagues found that alcohol could lead to positive effects from lighter drinking episodes, but negative effects from heavier drinking episodes (Hodgins et al., 1995). The Global Burden of Disease study also found potential health benefits at the population level for those who consumed 1-2 drinks per day or less (Bryazka et al., 2022). Coffee consumption may exhibit frequency-based hormesis, where moderate intake – around 2-3 cups per day – is associated with reduced risks of depression, anxiety, and even Alzheimer's disease, while excessive use can lead to addiction and withdrawal symptoms (Min et al., 2023; Zhu et al., 2023). It is also possible that common recreational drugs, such as psychedelics, have small benefits to self-perceived mental health when taken in low doses or at low frequencies, although the risks of addiction and possibly acute harm associated with such behaviours are high (T. Anderson et al., 2019; Kaypak & Raz, 2022; Polito & Stevenson, 2019).

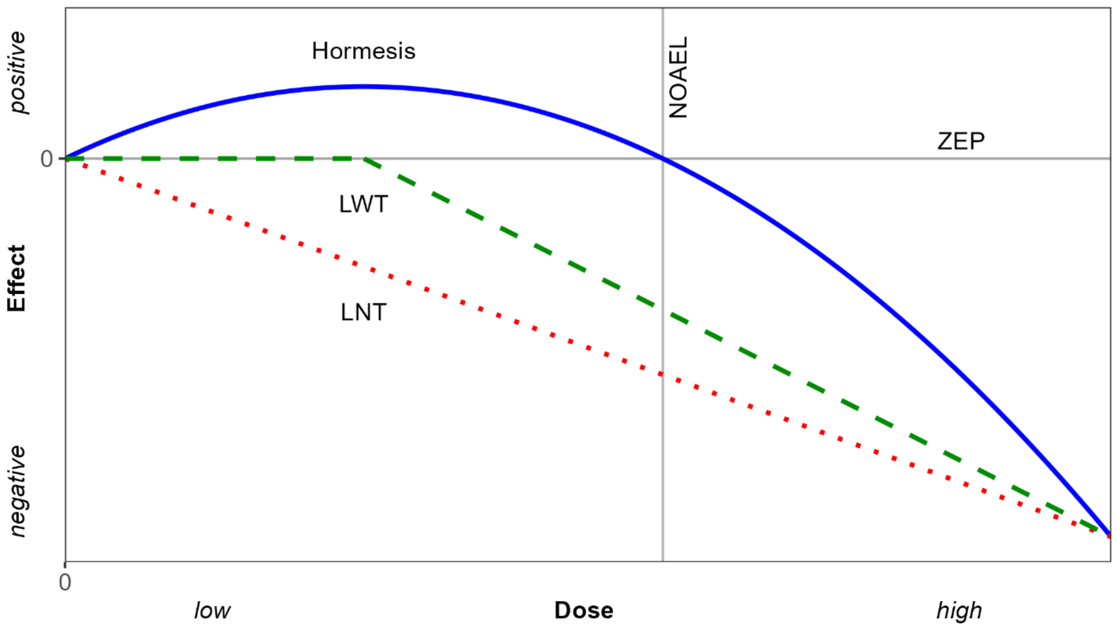


*Figure 6: Generic graphs of the Linear No Threshold model (LNT, dotted line), Linear With Threshold model (LWT, dashed line), and hormesis (solid line) for both drug-based and behavioural contexts. NOAEL = No Adverse Effect Level (also known as the hormetic threshold), presented for the hormetic curve only.*

Similarly, digital behaviours, such as the use of short-video applications like YouTube and TikTok, can lead to behavioural addiction and mental health issues if performed excessively; however, moderate use in the right contexts may yield social benefits (Brannigan et al., 2023; Ho et al., 2014; Przybylski & Weinstein, 2017; Zhang et al., 2023). Until recently, the relationship between digital content consumption and mental health was regularly explained by the 'displacement hypothesis' which suggested that exposure to digital technology is directly proportional to harm if it replaces 'healthier' activities (Neuman, 1988). More recently, the 'digital Goldilocks hypothesis' has proposed that moderate technology use benefits mental health by improving social connectivity, identity and skill development through platforms such as online gaming and social media (Etchells et al., 2016; Przybylski, 2014; Przybylski & Weinstein, 2017); however, excessive technology use might replace meaningful activities. Przybylski & Weinstein (2017) explicitly tested this theory in a preregistered study of a large sample of English adolescents (N = 120,115) and found that the relationship between screen time and mental health was best described using a hormetic curve; these results have since been replicated by Brannigan et al. (2023). Hence, this is one example of how digital content consumed within the healthy limit may have a negligible or even beneficial effect on the human's mental state, while exceeding this limit can have a negative impact on mental health.

It is possible that the hormetic model could provide an accurate description of the relationship between frequency or quantity of use of pornography, and subsequent effects on mental health. In one cross-sectional study, Svedin et al. (2023) observed a U-shaped relationship between the frequency of pornography use in adolescent boys and mental health outcomes, with a higher risk of poor mental health for both infrequent watchers (never or once/twice a year) and frequent watchers (weekly or daily) compared to moderate watchers (a few times each month). However, while there is some data examining how the frequency and quantity of pornography use affect mental health (Bőthe, Tóth-Király, Potenza, et al., 2020; Chen, Jiang, Wang, et al., 2022; Cui et al., 2021; Huțul & Karner-Huțuleac, 2024), our understanding of the causal mechanisms behind these relationships is poor. If the hormetic model applies to certain individuals, it implies that there may be a NOAEL, or healthy limit, of pornography use for those individuals, which may be moderated by factors such as moral incongruence. I explore the theoretical implications of this model further in Chapters 5 and 6.

**Pharmacokinetic/Pharmacodynamic (PK/PD) Modelling**

One possible paradigm for analysing the neurophysiological effects of pornography use is pharmacokinetic/pharmacodynamic (PK/PD) modelling, which is essential for understanding drug interactions with biological systems and determining appropriate drug dosages in pharmacotherapeutic treatments (Rajman, 2008). By integrating pharmacokinetics, which studies the absorption, distribution, metabolism, and excretion of a drug, with pharmacodynamics, which examines the drug's biological effects (Meibohm & Derendorf, 1997), PK/PD modelling provides a biologically grounded mathematical framework to describe and predict the time course of drug concentrations and their effects, providing an advantage over generic control theoretic approaches that lack this biological grounding. The PK/PD approach is widely used in drug development to predict drug effectiveness before clinical trials, optimise dosing regimens, and enhance therapeutic outcomes. A more comprehensive overview of PK/PD modelling is provided by Csajka & Verotta (2006) and Upton & Mould (2014).

While PK/PD modelling is typically used to measure the body's response to pharmacological drugs, it also has the potential to be used for modelling the neurohormonal effects of pornography use. The acts of sexual intercourse and masturbation produce a sequence of physiological, hormonal and emotional changes known as the sexual response cycle (Masters & Johnson, 1966; McNabney et al., 2020). While studies have examined this cycle in some depth for partnered sex, there is scarce literature comparing the long-term after-effects of partnered sex versus solo masturbation or pornography use. However, some promising work has been done measuring the neuroendocrine response to different types of sexual activity in the laboratory. For instance, studies by Krüger and colleagues (Brody & Krüger, 2006; T. Krüger, Haake, Chereath, et al., 2003), have shown that sexual intercourse is associated with temporary spikes in plasma epinephrine and norepinephrine levels during orgasm, followed by a surge in prolactin; notably, prolactin levels after intercourse are up to 400% higher compared to those following masturbation, which may lead to reduced sexual drive and function (T. Krüger, Haake, Haverkamp, et al., 2003).

Characterizing the pharmacokinetics of pornography use with PK/PD modelling has its limitations, particularly if we wish to examine the role of moral incongruence in a controlled environment such as a laboratory. As an example, take an experiment in which participants are exposed to different types of images, some of them pornographic, and asked how much guilt or shame they experience when viewing those images. Such an environment may influence participants' feelings of guilt, as they could rationalise their actions by attributing responsibility to the researcher evaluating them. This dynamic could reduce the emotional impact typically linked to moral incongruence because one's sense of personal choice – central to feelings of guilt and shame – would likely be diminished when participants perceive that they are simply following instructions rather than acting autonomously. Yet it may be possible to infer the pharmacokinetics of pornography use in a less obtrusive, more observational way, by measuring the pharmacodynamic outcomes of pornography use in the form of externally measurable psychological variables via EMA – an approach that has not yet been explored in the literature. By characterising the pharmacodynamic profile of pornography use over time (in other words, *the temporal dynamics associated with pornography use*), it may also be possible to predict the levels at which pornography use becomes harmful, as well as the degree of harm. If successful, this modelling could potentially be applied to other behavioural disorders also, such as gaming, gambling, or Internet addictions.

**Mathematics of PK/PD Modelling**

At the core of PK/PD modelling is the pharmacokinetic model, which can be described using ordinary differential equations (ODEs). A common model is the one-compartment model with first-order absorption and elimination. The ODE describing drug concentration over time, $C(t)$, in a single compartment with clearance (such as the vascular system) is:

$$\frac{dC(t)}{dt} = -k_e C(t)$$

where $k_e$ is the elimination rate constant, which is related to the clearance rate ($Cl$) and the volume of distribution ($V$) by:

$$k_e = \frac{Cl}{V}$$

If the drug is infused into $V$ at a constant rate $R$ during the time interval $[0, T_{infusion}]$, the system can be described by the following piecewise function:

$$\frac{dC(t)}{dt} = \begin{cases} \frac{R}{V} - k_e C(t); C(0) = 0, & 0 \leq t \leq T_{infusion} \\ -k_e C(t); C\left(t - T_{infusion}\right) = C(T_{infusion}), & t > T_{infusion} \end{cases}$$

Solving using the integrating factor method and the initial conditions above, we obtain the following piecewise equations describing the decay of drug concentration over time both during and after drug infusion:

$$C(t) = \begin{cases} \frac{R}{k_e V}\left(1 - e^{-k_e t}\right) + C_0 e^{-k_e t}, & 0 \leq t \leq T_{infusion} \\ C_{T_{infusion}} e^{-k_e (t - T_{infusion})}, & t > T_{infusion} \end{cases}$$

For a more detailed mathematical derivation that includes repeated drug dosing, please refer to Savva (2022). An example simulation of this model for repeated drug doses is demonstrated in Figure 7, with varying clearance rates.

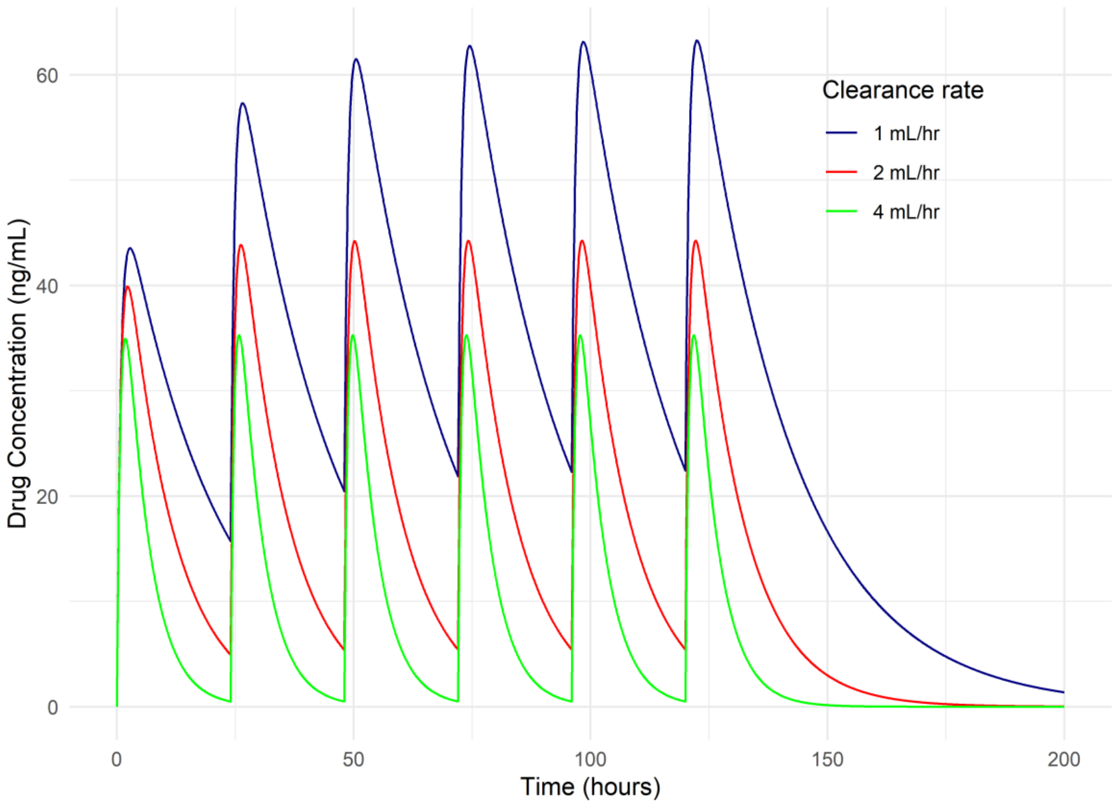


*Figure 7: Pharmacokinetics of a one-compartment model with 6 repeated drug doses and varied clearance rates. Volume of compartment is 20 mL. An approximate steady-state (where the rate of drug clearance is matched by the rate of drug infusion) is reached for all simulations, albeit more quickly at higher clearance rates.*

On the other hand, pharmacodynamic models describe the relationship between drug concentration and its therapeutic effect. One commonly used model is the Hill equation, which characterises the effect $E$ of a drug concentration $C$:

$$E = E_0 + \frac{E_{max} C^n}{EC_{50}^n + C^n}$$

where $E_0$ is the baseline effect, $E_{max}$ is the maximum possible effect, $EC_{50}$ is the concentration of the drug that produces 50% of $E_{max}$, and $n$, the Hill coefficient or sigmoidicity parameter, governs the steepness of the concentration-effect curve (also known as the biophase curve) (Gesztelyi et al., 2012; Goutelle et al., 2008). Figure 8 demonstrates the effects of modifying each of these parameters, highlighting the flexibility of the Hill equation for modelling various pharmacodynamic effects.

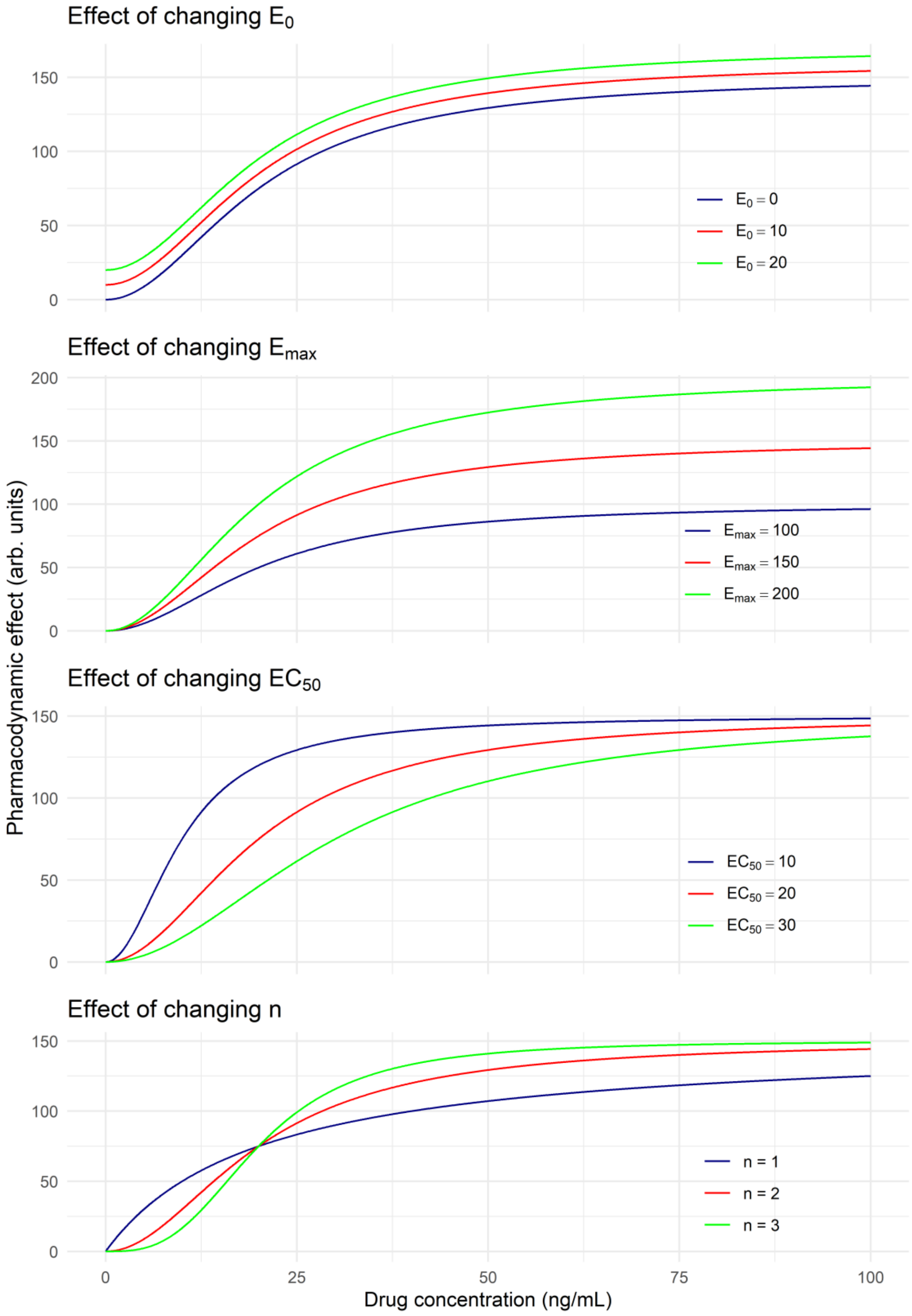


*Figure 8: Effect of changing various parameters in the Hill equation, changing the relationship between drug concentration and physiological effect. Default parameters unless otherwise specified are:* $E_0 = 10, E_{max} = 150, EC_{50} = 20, n = 2$.

## Affective Chronometry, and Ecological Momentary Assessment (EMA)

Evaluating the temporal dynamics of pornography use – whether through PK/PD modelling or via neurological examination methods such as functional magnetic resonance imaging (fMRI) – presents numerous challenges. Several studies have attempted to measure neural correlates and other salient features of hypersexuality in laboratory settings. These studies have largely involved participants examining visual sexual stimuli while undergoing fMRI measurements, or similar, with inconsistent results that have yielded evidence both for and against the classification of Compulsive Sexual Behaviour Disorder (CSBD) as a behavioural addiction (e.g., Gola et al., 2016; Prause et al., 2015; Prause & Pfaus, 2015; Steele et al., 2013; Voon et al., 2014). Some of this research aligns with the incentive salience theory of addiction, suggesting that in CSBD, 'wanting' becomes dissociated from 'liking', possibly due to pornography-induced hypersensitivity of the mesocorticolimbic circuitry in the brain, which links incentive salience with reward-associated stimuli (Berridge et al., 2009; Brand, Snagowski, et al., 2016; Gola et al., 2016; Robinson & Berridge, 1993, 2008; Voon et al., 2014). However, opponents of this view suggest that these studies have methodological limitations, failing to differentiate between high sexual desire and true compulsivity, and that pathologizing sexual behaviour may stem more from cultural or religious values than from empirical evidence of harm or loss of control (Ley et al., 2014; Prause et al., 2015).

While the debate continues, the applicability of these findings to assessing the validity of either the pornography addiction model or the moral incongruence model of PPU is questionable. Gola et al. (2016) have argued that many of these studies demonstrate that visual sexual stimuli play the role of reward in a laboratory, whereas in real life, the stimuli play the role of cue leading to sexual arousal, with orgasm being the reward (Gola et al., 2016). As mentioned previously, a primary concern is that pornography use in a natural environment, typically at home, cannot be accurately replicated in laboratory experiments, nor can it accurately reproduce feelings of moral incongruence. In a laboratory, participants are under the guidance of a researcher, and may not experience self-imposed moral conflict in the same manner. This discrepancy can be attributed to two factors. Firstly, individuals struggling with PPU are less likely to voluntarily expose themselves to sexual stimuli in laboratory conditions, leading to selection bias. Secondly, participants may attribute any feelings of moral incongruence to the experimenter's instructions rather than their own decisions. In natural conditions, individuals are more likely to experience moral conflict due to a perceived inability to control urges to use pornography, a sensation that laboratory conditions cannot accurately reproduce. Consequently, it can be argued that only ecological studies conducted in natural settings have the capacity to truly quantify the temporal dynamics of individuals grappling with PPU, even if this limits our ability as researchers to observe the neural correlates of these behaviours.

One such ecological approach, known as Ecological Momentary Assessment (EMA) or the Experience Sampling Method (ESM), is a longitudinal methodology that collects real-time data from participants about their thoughts, feelings, or actions, often multiple times a day, in their natural environment (Bos et al., 2015; Lukasiewicz et al., 2007; Shiffman & Stone, 1998). These methodologies are part of the family of approaches known as daily life survey methods (Mehl et al., 2012). EMA minimises recall bias by capturing information close to the event occurrence (Beal & Weiss, 2003; Shiffman et al., 2008; Shiffman & Stone, 1998). This makes it ideal for measuring temporal dynamics, as emotional states are difficult to remember several hours later (Bresin et al., 2024; Shiffman et al., 2008; Voogt et al., 2013). Such measuring of affective dynamics over time is also known as 'affective chronometry' (Botelho et al., 2018; R. J. Davidson, 1998; Dejonckheere et al., 2020; Feidakis, 2011), and provides more accurate quantification of behaviour-affect relationships, especially when these relationships are strongest shortly after the behaviour occurs (Bresin et al., 2024). For instance, Heller et al. (2015) used EMA to track how positive emotions faded after participants received monetary rewards, showing that these emotions decayed exponentially over time, which has implications for the underlying neurohormonal components that produce these emotions (Ibarra et al., 2020).

EMA data provides researchers with the ability to imply Granger causality – in other words, the capacity to determine whether one variable can predict another over time (Granger, 1969) – by analysing variables that are temporally correlated. This can be accomplished using techniques such as the Random Intercept Cross-Lagged Panel Model (RI-CLPM) (Hamaker et al., 2015), vector autoregression (VAR) techniques such as AutoVAR (Krieke et al., 2015), a logistic autoregression model (ALARM) for binary data (Agaskar & Lu, 2013), or Peter and Clark Momentary Conditional Independence (PCMCI) (Huckins et al., 2020). However, these methods don't provide a framework for hypothesizing and testing specific decay patterns of temporal dynamics, preventing us from inferring the underlying causal mechanisms that may produce these patterns.

An EMA could, in theory, provide the time series data necessary to test for causal relationships between pornography use and mental health (Huckins et al., 2020). Similar analyses have been performed using EMA data previously, although most commonly with a pharmacological focus. For example, a systematic review of 91 studies investigating substance users found that EMA analyses provided strong evidence for a relationship between craving and substance use, which had been challenging to establish due to statistical limitations, such as the timing of assessments (Serre et al., 2015). In their review of psychopharmacological EMA analyses, Bos et al. (2015) highlighted 18 studies that examined the effects of medication on major depressive disorder, substance use disorders, anxiety disorders, psychotic disorders, and eating disorders. EMA has also been used to analyse relapse patterns for addictive substances in various contexts (Comulada et al., 2016; Paolillo et al., 2018).

EMA studies on pornography users have been performed previously (Bőthe et al., 2021; Wordecha et al., 2018), although with some limitations. For example, Wordecha et al. performed an EMA on subjects struggling with pornography binges, and found that a sampling frequency of once per day was too low to test for a causal relationship between variables such as mood, anxiety, stress, and binge pornography use (Wordecha et al., 2018). Their recommendation was to take a few samples per day to improve data quality, which aligns with other studies (Kockler et al., 2018; Koenig et al., 2021). Only one other study ('Hands-off') has tracked mental health scores related to pornography use, but this was a secondary outcome, and the study relied on a web-based application – not a mobile one – which led to high attrition rates (Bőthe et al., 2021). In Chapter 6, I will demonstrate how the learnings from these studies were utilised in the design of an EMA study to analyse the temporal dynamics of pornography users.

**EMA Protocol Design**

Capturing emotional data with EMA presents many challenges. EMA data can be collected either immediately or following a time delay; sampling the immediate experience eliminates recall bias and increases precision but may not accurately reflect the entire experience of the subject (J. A. Henry et al., 2012). On the other hand, sampling for a recollected interval of experiences (such as the past day) may increase accuracy by reflecting the broad strokes of the emotional experience, providing the researcher with more information overall. However, this adds recall bias and increases measurement uncertainty (J. A. Henry et al., 2012).

The researcher must also consider statistical power and precision based on the number of measurements they expect to capture (Wrzus & Neubauer, 2022). Burke et al. found that for high-frequency EMA, participant prompts should be limited to a maximum of five per day to maintain high compliance rates; they also found that responses to random prompts were higher than for end-of-day prompts (Burke et al., 2017). This rate of five per day has been regularly observed in other studies, although there are notable exceptions that still have high compliance rates (Wrzus & Neubauer, 2022). For example, participants have been known to respond to a survey frequency of once every 17 minutes for four consecutive days (Kuppens et al., 2010), while others have responded to daily surveys for up to six months (Epstein & Preston, 2012). However, a systematic review of EMA analyses found evidence that the compliance rate did not change with the number of assessments per day, but did change with increasing study length, particularly those longer than one week (Wrzus & Neubauer, 2022). Some studies have countered this by scheduling break days in between assessment days (Neubauer et al., 2018; Riediger et al., 2009).

The annual Pornhub ‘Year in Review’ article (*The 2019 Year in Review – Pornhub Insights*, 2019) indicates that pornography consumption on the website pornhub.com is lowest early in the morning, has a small spike around mid-afternoon, and then spikes again following 9 pm, with the heaviest consumption occurring between the hours of 10 pm and 2 am. This pattern appears consistent across weekdays (*The 2019 Year in Review – Pornhub Insights*, 2019) and is replicated by a web traffic analysis of approximately 15,000 broadband subscribers over a three-year period by Morichetta et al. (2021). Hence, the timing of any EMA surveys should be adjusted to ensure enough data is captured during high pornography use times.

**Summary**

The theoretical framework of opponent process theory may offer valuable insights into the nature of PPU and its effects on mental health outcomes. This enhanced comprehension, in principle, should augment our capacity to discern which theoretical model most accurately characterises PPU. Consequently, this refined theoretical grounding may aid the development and implementation of more efficacious therapeutic interventions for individuals with PPU.

Chapter 5 introduces behavioural posology, a novel modelling approach that integrates these methods to quantify the temporal dynamics of behaviours such as pornography use, aiming to identify the healthy limits of pornography use for different individuals based on their level of moral incongruence. Chapter 6 builds on this by presenting results from an EMA study of pornography users, offering empirical data to validate aspects of the behavioural posology model and further clarify the relationship between pornography use and mental health indicators. In Chapter 7, the findings from these Chapters are then integrated with the content analysis from Chapter 3 to demonstrate how a deeper understanding of PPU's temporal dynamics can lead to better classification of PPU as a disorder, potentially leading to improved treatment options in future for those affected by PPU.

# Chapter 5: Behavioural Posology Study

## Prelude

The mathematical and methodological techniques outlined in Chapter 4 offer a toolkit for collecting high-frequency longitudinal data and model the temporal dynamics associated with repeated behaviours. In particular, the use of pharmacokinetic/pharmacodynamic (PK/PD) modelling provides a biologically grounded methodology for simulating the time-varying nature of affective states in relationship to behavioural events. This offered me a unique approach to developing an opponent process theory of pornography use, potentially providing insights that could be integrated into future mobile apps for managing PPU.

Yet while developing this opponent process model, I realised that it also had the potential to bridge the divide between some opposing schools of thought in the research literature, which remains quite polarised. Some researchers view the concern over pornography as an unnecessary moral panic, while some see it as harmful to certain individuals but not to others, and some believe it is always detrimental. A more balanced perspective might be that even behaviours considered 'harmless' can become problematic if performed excessively, to the extent that they interfere with one's mental health and displace other activities. If this view is correct, it suggests a healthy limit, or No Adverse Effect Level (NOAEL), that separates harmless (and possibly healthy) use from harmful use. Pornography use beyond this limit could indicate addiction if the user believes it is out of their control (M. Griffiths, 2005). However, we know that people who experience high levels of moral incongruence may experience feelings of distress even at low frequencies of pornography use (Grubbs, Perry, et al., 2019a), indicating that for these people, the healthy limit of use may be lower than average – or, in some cases, zero use.

By studying the underlying temporal dynamics of PPU, I aimed to glean insights into any potential affective states, cravings, and withdrawal symptoms associated with pornography use, in order to better understand the healthy limit of pornography use for different individuals. It was hoped that this would also aid in the classification of PPU as either an obsessive-compulsive disorder, an impulse-control disorder, or an addiction. However, to achieve this, I needed a quantitative paradigm to develop the opponent process model of pornography use in such a way that the model could also be used as a theoretical basis for hypothesis testing.

As such, behavioural posology is my attempt to create a modelling paradigm to understand the temporal dynamics associated with behaviours for any individual. In this context, 'behaviours' range from relatively harmless behaviours with small or negligible b-processes (like laughter, chewing gum, or reading) to those with clear negative b-processes that worsen with high-frequency repetition (like lying, gambling, committing crimes, or using a highly addictive drug such as heroin). This method applies a theoretical pharmacology-based approach to psychology to understand the neurohormonal effects of these behaviours. In this case, I hypothesised that pornography use is linked to affective states through an opponent process mechanism and tried to simulate these processes using PK/PD modelling methods.

A key aspect of this approach is an analysis technique called Behavioural Frequency Response Analysis (BFRA). In essence, this applies dynamic systems analysis to analyse the cumulative effects of opponent processes induced by behaviours. Additionally, this approach sheds light on Solomon and Corbit's 'standard pattern of affective dynamics', (Solomon & Corbit, 1974) enhancing the credibility of the paradigm and opening new research opportunities into the neurodynamics of affect.

***Manuscript***

The manuscript from this Chapter has been published in the journal 'Advanced Theory and Simulations'.

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 Minor grammatical adjustments have been made to ensure consistency with the remaining thesis.

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**Behavioural Posology: A Novel Paradigm for Modelling the Healthy Limits of Behaviours**

*Abstract*

One of the challenges faced by behavioural scientists is the lack of modelling methodologies for accurately determining when a behaviour becomes problematic. The authors propose ‘behavioural posology’ as a novel modelling paradigm for quantifying the healthy limits of behaviours through the concept of behavioural dose. As an example of this paradigm, a pharmacokinetic/pharmacodynamic model of a hypothetical digital behaviour is presented, based on opponent process theory. The generic model can be adapted to simulate Solomon & Corbit’s model of affective dynamics from 1974, and the model predicts features of addiction such as hedonic allostasis, withdrawal, and apparent tolerance. A Behavioural Frequency Response Analysis of the model demonstrates how behavioural repetition may result in a hormetic dose-response relationship that depends on the frequency of the behaviour. The model can be experimentally validated using Ecological Momentary Assessment, allowing researchers to hypothesise, model, and test plausible mechanisms for behavioural addictions and compulsions. The potential for behavioural posology to be applied as a clinical support tool in psychological medicine is discussed, as this modelling framework may help to detect and limit behaviours being performed too frequently based on factors such as the person’s moral beliefs.

*Introduction*

**The Rationale for Behavioural Posology**

Posology is the study of dosage. It is mainly used for optimizing therapeutic drug administration, but has also been used to establish safe doses for illicit drugs in therapeutic contexts, such as cannabis (Giorgi et al., 2020; Lafaye et al., 2017) and lysergic acid diethylamide (LSD) (Kaypak & Raz, 2022). Evidence suggests that behavioural and drug addictions have a similar aetiology and symptomology (Grant et al., 2006; M. Griffiths, 2005; Koob & Moal, 2008; Robinson & Berridge, 2008), indicating that a posological paradigm could be applied to study the temporal nature of behavioural addictions – particularly those of a digital nature.

Many mental health disorders have been linked to the excessive use of technology. Examples include increased rates of depression and anxiety in high users of social media (Keles et al., 2020), smartphones (Elhai et al., 2017), gaming (Wang et al., 2017), pornography (Borgogna & McDermott, 2018; Butler et al., 2018; Harper & Hodgins, 2016; Kraus et al., 2015; Okabe et al., 2021), and Internet-related behaviours in general (Brand, Young, et al., 2016). Still, there is debate over whether behaviours such as compulsive pornography use can be classified as addictive, due to insufficient evidence of causal directionality between the behaviours and their associated mental states (Gola et al., 2017; Kafka, 2014; Krueger, 2016; Reid et al., 2012).

Some causal mechanisms for depression induced by repeatable behaviours have been proposed. For example, correlational studies show that people who morally disapprove of pornography but continue to use it experience greater levels of depression, anxiety, and distress (Grubbs, Floyd, et al., 2022; Grubbs, Perry, et al., 2019a; Grubbs & Perry, 2019; Lewczuk et al., 2021). Moral incongruence can be defined broadly as the feelings of distress, guilt and shame experienced when one performs a behaviour that violates one's moral code (Grubbs, Perry, et al., 2019a). Lewczuk et al. (2021) highlighted the potential role of moral incongruence in self-perceived addiction to the Internet, social networking, and online gaming. Further, Grubbs et al. (2022) found that the interaction of behavioural frequency and moral incongruence predicted self-perceived addiction to behaviours like pornography use and gambling; however, the same has not been found for illicit substances, tobacco, or prescription drugs, and results were inconclusive for alcohol and marijuana use. The authors noted that while context matters, "moral disapproval consistently predicted self-reported addiction to all focal behaviours and substances, with effect sizes in the medium-to-large range" (Grubbs, Floyd, et al., 2022, p. 756). Still, the neuropsychological mechanisms behind this interaction are poorly understood, due in part to a lack of longitudinal data and insufficient causal modelling techniques. In particular, there is no clear method for quantifying whether a person's behavioural patterns have led to long-term mood modification, increased tolerance, or withdrawal – some of the key components of addiction (M. Griffiths, 2005).

This article proposes a novel modelling paradigm called 'behavioural posology' to analyse these temporal relationships, in order to find the healthy limits of behaviours. This paradigm may assist researchers in hypothesizing causal models of addiction and has the potential to be applied broadly in the field of behavioural sciences. I demonstrate an example of this method by modelling the relationship between a repeated digital behaviour and hedonic states. I also discuss how to validate this model experimentally. But first, it is important to explain the historical background of this model.

## Theoretical Background

***Opponent Process Theory.*** Solomon & Corbit's opponent process theory suggests that repeated behaviours can lead to allostasis, a condition where an individual's set point becomes dysregulated and shifts away from homeostatic levels, often leading to a depressed hedonic state (Solomon & Corbit, 1974). In this theory, the initial euphoric response to a behaviour, experience, or drug is known as the 'a-process'. This is followed by a compensatory opposite reaction, or 'b-process', which consists of a more extended period of negative hedonic state – typically associated with craving and withdrawal – after which homeostasis is restored (Solomon & Corbit, 1974). Repeating the opponent processes at high frequency prevents recovery to homeostasis due to the slow decay and additive nature of the b-process (Koob & Le Moal, 2001; Solomon & Corbit, 1974) leading to a gradual slide into a depressed mood. While this theory has been broadly accepted, much remains unknown about the psychological and pharmacological mechanisms behind opponent processes.

***Pharmacokinetic/Pharmacodynamic Modelling of Opponent Processes.*** The way the body processes a drug (its pharmacokinetics) and the drug's effect on the body (its pharmacodynamics) can be simulated using pharmacokinetic/pharmacodynamic (PK/PD) modelling. Clinicians use this tool to optimise drug dose regimens (Schulthess et al., 2018). Most PK/PD models rely on the Hill equation to quantify the relationship between a drug's concentration in the body and its pharmacodynamic effects – also known as the biophase curve – which provides a greater understanding of drug-receptor interactions and their effects on mental states (Gesztelyi et al., 2012; Goutelle et al., 2008). A full explanation of the technique is outside the scope of this article, but for those unfamiliar with PK/PD modelling, I recommend Upton and Mould's introductory papers (Mould & Upton, 2012, 2013; Upton & Mould, 2014).

Opponent process theory assumes that the b-process is pharmacokinetically derived from the a-process. For example, if the a-process is caused by dopamine release, then the b-process could be at least partly due to dopamine depletion of equal and opposite magnitude (Chou & D'Orsogna, 2022). However, the neurochemical and hormonal cascades for most opponent processes are generally more complex. It's also possible that the dose-effect relationships for the a-process and b-process are not identical, meaning that different behaviours could lead to varying rates of allostasis and depression based on the Hill equation parameters for the opponent processes generated by the behaviour.

In theory, the effect of any chemical or behavioural stimulus on the body can be modelled as a PK/PD process, even for a-processes with no opposing after-reaction. For example, laughing or cuddling can produce a pleasurable reaction – due to the release of endorphins and oxytocin – with a negligible opposing response (Morrison, 2016; Yim, 2016), making it very difficult to observe allostasis. Yet allostasis may still be achieved with very high behavioural frequencies. Laughter-induced syncope, a rare phenomenon where a person can faint from excessive laughter, is a possible example of this (Topno & Thakurmani, 2020).

Since the b-process decays more slowly than the a-process, moderators of the b-process have the greatest effect on the rate of hedonic allostasis (i.e., the rate at which the subject's mean hedonic state decreases), as shown by Ahmed and Koob's modelling (2005). In another example, Chou and D'Orsogna (2022) proposed a link between neuroticism and the b-process for certain behaviours, showing that a larger b-process produces greater levels of craving, which could lead to addiction. A similar mechanism can be applied to the moral incongruence model of behavioural addiction to simulate a subject's slide into depression via allostasis.

***Frequency Response Analysis.*** From this, a question arises: can we determine the frequency at which any behaviour becomes harmful to the user based on their moral beliefs about the behaviour? To answer this, we must first understand the concept of hormesis: a biphasic dose-response relationship where low doses of a stimulus have a positive effect on the organism, while high doses have a negative effect (Agathokleous et al., 2020). Numerous examples of hormesis exist in nature (Calabrese & Blain, 2005; Schirrmacher, 2021), medicine, and psychology, such as the Goldilocks zone (Alleman et al., 2014), the Yerkes-Dodson law (Calabrese, 2008c), and the therapeutic window (Calabrese, 2008b).

The hormesis literature generally focuses on the dose-response relationship for single doses (Calabrese, 2008a). For example, Calabrese has suggested that hormesis is a commonly observed dose-response pattern in addictive drugs, focusing on the relationship between dose concentration and rat locomotor activity (Calabrese, 2008a). However, this approach may not accurately predict the effects of dose schedules. In their review of hormetic phenomena, Li et al. (2019, p. 954) stated that "the temporal pattern and duration of the exposure are underappreciated factors in determining the net outcome. Intermittent exposure often generates opposite effects as compared to continuous exposure".

Therefore, in a behavioural context, one should analyse low and high behavioural frequencies to see whether the relationship between behavioural frequency and effect is linear (e.g., LNT) or non-linear (e.g., LWT or hormesis). This can be assessed using frequency response analysis, a signal processing technique that involves creating Bode plots to show a system's response to inputs of different frequencies (Schulthess et al., 2018). This method has already been applied in biological contexts. Schulthess et al. (2018) proposed that dosing frequency could be modulated to affect the pharmacodynamic response and demonstrated four pharmacological problems where frequency response analysis could be used to optimise drug treatment regimens. Mitchell et al. (2015) discovered an optimal frequency of oscillation for a mitogen-activated protein kinase signalling network in yeast; above and below this frequency, the response was dampened. Radiotherapy is another field in which the frequency of radiation dose delivery significantly impacts therapeutic outcomes (McMahon, 2018).

I propose that one can observe hormesis in behaviours by changing their frequencies and observing the hedonic outcomes, as part of a Behavioural Frequency Response Analysis (BFRA). Assuming a hormetic relationship, positive long-term hedonic outcomes will be observed at low behavioural frequencies, but negative long-term outcomes will occur at higher frequencies.

Therefore, one can use a BFRA to identify the behavioural frequency range that produces positive long-term hedonic outcomes for individuals.

***Modelling Behavioural 'Dose'.*** Using a 'black box' approach, it is possible to infer a drug's properties by evaluating its effects on a person's mental state over time. In other words, one can reverse engineer the pharmacokinetics of a drug – how the body processes it – from its pharmacodynamic effects on the brain (Csete & Doyle, 2002; Eisenberg, 2007; Newlin et al., 2012; Upton & Mould, 2014). This approach is often used when it is too difficult to measure the underlying biological mechanisms of a drug (Dumas & Pollack, 2008). Similarly, it may be possible to use this approach to understand the effects of performing a behaviour on one's mental state.

To do this, behavioural 'dose' must first be defined. A concept analysis by Manojlovich & Sidani (2008) found that four attributes can describe the 'dose' of an intervention: purity, amount, frequency, and duration (McVay et al., 2019; Voils et al., 2012). By reframing 'intervention' as behaviour' (Voils et al., 2014) and 'purity' (i.e., concentration) of dose as 'potency' of the behaviour (Hoza et al., 1992), we can similarly define behavioural dose. For example, 'video gaming dose' can be determined by recording the following metrics:

- $Potency$: the level of immersion or engagement in the behaviour (e.g., a game played on a high-end gaming console is likely to provide greater immersion than the same game played on a smartphone)
- $Amount$: the time spent performing the behaviour (e.g., length of a gaming session)
- $Frequency$: how often the behaviour is performed within a specific period (i.e., $Duration$).

Then, the gaming dose for a single session can be calculated as follows:

$$Dose_{individual\ session} = Potency \times Amount$$

and the total dose of cumulative gaming sessions within a specific period is:

$$Dose_{total} = Frequency \times Duration \times \overline{Dose_{individual\ sessions}}$$

where $\overline{Dose_{individual\ sessions}}$ represents the mean individual session dose for all gaming sessions over the $Duration$ in which $Dose_{total}$ is assessed.

Thus, we can perform a BFRA by treating $Potency$, $Amount$ and $Duration$ as constants and replacing $Dose$ with $Frequency$ on the x-axis of Figure 6 (which demonstrates the LNT, LWT, and hormesis models). However, this definition is problematic because it implies a fixed effect, when in fact the effect of behaviour on one's mental state varies over time. It also does not capture the complexity of multiple behavioural doses applied in rapid succession. To better model the cumulative effects of repeated doses, opponent processes generated by each behavioural session could be modelled using the PK/PD framework, and validated using experimental data.

In summary, it may be possible to detect healthy limits for certain behaviours by changing the frequency of behavioural doses and observing the effects on a person's mental state. This type of analysis can be performed using a modelling paradigm called behavioural posology. In this article, I will define behavioural posology and demonstrate its use by performing a Behavioural Frequency Response Analysis (BFRA) on a hypothetical digital behaviour to determine the healthy limits of that behaviour. I will also discuss how this model can be tested experimentally using an Ecological Momentary Assessment (EMA) study.

### *Methods*

#### Mathematical Model

I created a proof-of-concept PK/PD model of a digital behaviour to simulate Koob & Le Moal's conceptual framework of allostasis (Figure 4 of Koob & Le Moal, 2001), based on Solomon & Corbit's theory of opponent processes (Solomon & Corbit, 1974). I used the mrgsolve package (v1.0.9) in R v4.1.2 (Elmokadem et al., 2019; R Core Team, 2022) to code the model as a system of ordinary differential equations (ODE's). The base model (Figure 9) was a two-compartment pharmacokinetic model with zero order infusion (i.e., the behavioural dose directly induced a change in hormonal states, with no intermediate processing) and had a hedonically positive a-process. The model code is available on the Open Science Framework website at https://osf.io/sau4v/ (N. Henry, 2023).

The following assumptions were made, based on the principles of affective neuroscience and opponent process theory (Koob & Le Moal, 2001; Panksepp, 1998; Solomon & Corbit, 1974):

- A behaviour results from a stimulus that creates a desire for a state change.
- Conservation of energy and mass is observed, meaning that the pharmacokinetic concentrations of the a- and b-processes are linked.
- A neurochemical and hormonal response cascade at least partially drives the emotional response to this state change. An approximate model of the behaviour's effects doesn't require perfect knowledge of the sequence of hormones released.
- The initial a-process is followed by an oppositional b-process, which is caused by the depletion of the a-process hormones or the release of other hormones in response to the a-process.

- Behaviours have a complex relationship with internal and external events, which can generate either a positive or negative net hedonic outcome. For example, using social media to plan an activity with friends can promote long-term social bonding and generate a greater positive response than negative, resulting in a net positive outcome – despite the possibility that the person may feel some cravings for social media use afterward.

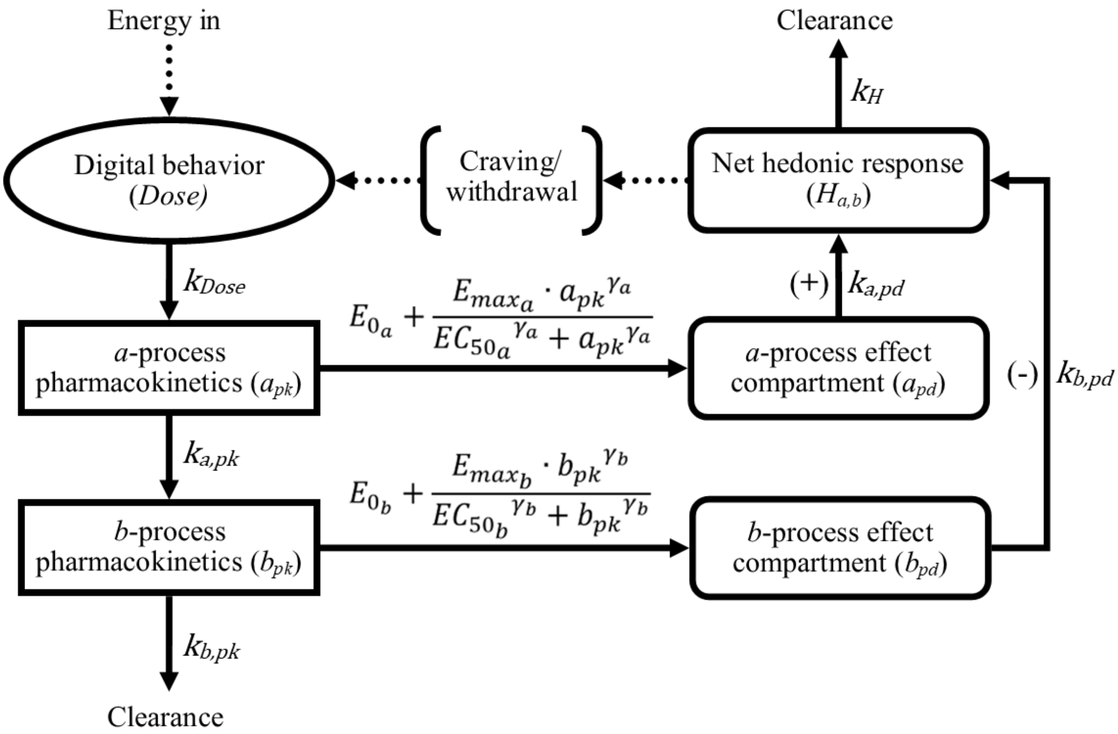


*Figure 9: Hypothesised compartment model representing the cycle of a repeated digital behaviour, potentially leading to addiction. Compartments linked by dotted lines were not modelled but demonstrate how the cycle of addiction could continue.*

In Figure 9, the PK compartments are the first to follow the $Dose$ compartment, and these represent the concentrations of neurochemicals and hormones released into the brain and bloodstream following the digital behaviour. The PD (or 'effect') compartments represent the intensity of the neurochemicals' effects on the body, for both the a- and b-processes (Meibohm & Derendorf, 1997). The relationship between the PK and PD compartments is governed by the Hill equation. The value of the 'net hedonic response' compartment is calculated as the sum of the opposing a- and b-process PD compartments and represents the brain's overall perception of the person's mood, or the 'manifest affective response' (Solomon & Corbit, 1974). For simplicity, I treated each of these compartments as discrete locations within the body. While multiple brain regions are likely to be involved in hedonic states, the model of opponent processes did not require these regions to be treated separately to produce useful results.

The equations for the base model are listed below. Due to the hypothetical nature of the model, I used arbitrary units for most variables, unless stated otherwise:

1) $$\frac{dDose}{dt} = -k_{Dose}Dose$$

2) $$\frac{da_{pk}}{dt} = k_{Dose}Dose - k_{a,pk}a_{pk}$$

3) $$\frac{db_{pk}}{dt} = k_{a,pk}a_{pk} - k_{b,pk}b_{pk}$$

4) $$\frac{da_{pd}}{dt} = E_{0_a} + \frac{E_{max_a} \cdot {a_{pk}}^{\gamma_a}}{{EC_{50_a}}^{\gamma_a} + {a_{pk}}^{\gamma_a}} - k_{a,pd}a_{pd}$$

5) $$\frac{db_{pd}}{dt} = E_{0_b} + \frac{E_{max_b} \cdot {b_{pk}}^{\gamma_b}}{{EC_{50_b}}^{\gamma_b} + {b_{pk}}^{\gamma_b}} - k_{b,pd}b_{pd}$$

6) $$\frac{dH_{a,b}}{dt} = k_{a,pd}a_{pd} - k_{b,pd}b_{pd} - k_H H_{a,b}$$

where $t$ is the time elapsed, in minutes; $Dose$ is the compartment for hormonal and neurochemical concentrations following digital technology use; $a_{pk}, b_{pk}, a_{pd}$ and $b_{pd}$ are the pharmacokinetic $(pk)$ and pharmacodynamic $(pd)$ compartments for the a- and b-processes; $k_{Dose}$, $k_{a,pk}$ and $k_{b,pk}$ are the clearance rates for the pharmacokinetic compartments; $k_{a,pd}, k_{b,pd}$ and $k_H$ are the clearance rates for the pharmacodynamic compartments; $E_0, E_{max}, EC_{50}$ and $\gamma$ are the coefficients of the Hill equation governing the shape of the biophase curve and the relationship between PK and PD, where $E_0$ represents baseline effect, $E_{max}$ represents the maximum possible effect, $EC_{50}$ represents half-maximal effect, and $\gamma$ is the sigmoidicity parameter describing the steepness of the biophase curve; and $H_{a,b}$ is the hedonic response compartment. At time $t = 0$, the values of the compartments were set as follows: $Dose(0) = 1, a_{pk}(0) = 0, b_{pk}(0) = 0, a_{pd}(0) = 0, b_{pd}(0) = 0,$ and $H_{a,b}(0) = 0.$ To simplify the initial model, I set the clearance rates of the pharmacodynamic compartments $(k_{a,pd}, k_{b,pd}, k_H)$ as constants equal to 1. When $a_{pd}$ > $b_{pd}$, the manifest affective response was denoted as the A-state, and when $a_{pd}$ < $b_{pd}$, the response was denoted as the B-state.

I used Solomon & Corbit's 'hedonic scale' of affect (Solomon & Corbit, 1974) as the primary outcome variable, with a value of 0 representing a neutral mood. The pharmacodynamic effects of the behaviour were described as transit compartments following their pharmacokinetic compartments. Input dose was distributed over a variable length of time, known as the infusion time, or time during which the behaviour was performed. The initial model had a one-minute infusion time, which was near-instantaneous on the timescale used. To achieve a steady-state response at each behavioural frequency, I kept $Dose_{individual\ session}$ constant for each simulation. This allowed me to perform a BFRA that focused purely on the effects of modifying $Frequency$.

Parameters were arbitrarily chosen to mimic the exponential decay of dopamine release and clearance in the brain as measured and modelled by Everett et al. (2022) and Chou & D'Orsogna (2022). I adjusted the Hill equation for both a- and b-processes so that the relationship between dose and effect for both processes was approximately linear for most of the plausible range of dose concentrations. I chose a high ratio of PK:PD magnitudes to simulate realistic opponent process dynamics, but other parameter sets would likely achieve similar dynamics. My main interest was how the a- and b-processes influenced hedonic outcomes, rather than the relationship between PK and PD. Therefore, I set $k_{a,pd}, k_{b,pd}$ and $k_H$ as constants equal to 1, and only changed the pharmacokinetic clearance rates (and $EC_{50_b}$) to adjust the a- and b-process magnitudes.

The parameter $\gamma_b$ was set to 2, representing positive cooperativity, to produce allostatic effects and apparent tolerance without requiring a feedback loop. The Hill equation for the a-process was relatively insensitive to the $\gamma_a$ parameter, due to the size of $E_{\max_a}$. Hence, I treated both the a-process and b-process as having identical $\gamma$ values. However, the pharmacokinetic compartment for the b-process ($b_{pk}$) had a slower evolving curve because it had a lower clearance rate than the a-process (i.e., $k_{b,pk} < k_{a,pk}$).

In simpler terms, the model was designed to simulate a hypothetical dose of a digital behaviour that generates a short, intense burst of pleasure-inducing hormones during the behaviour and a longer period of decreased hormone release and increased craving after the behaviour ends. This response cycle has a shorter, more intense a-process than Koob & Le Moal's model (Figure 4 of Koob & Le Moal, 2001), which is plausible for behaviours like pornography and social media use, where the a-process has a short duration, while the b-process is likely to be longer and less intense.

Our model was optimised to predict short- to medium-term hedonic outcomes over a range of days. For this reason, I did not include the 'Craving/withdrawal' compartment in the model, which would have turned it into a stochastic closed-loop model (e.g. see Bobashev et al., 2017; Chou & D'Orsogna, 2022; Newlin et al., 2012). Instead, for simplicity, I calculated net hedonic effects at constant behavioural frequencies, replacing the 'Craving/withdrawal' compartment with a constant frequency input to the $Dose$ compartment.

### BFRA of PK/PD Model

I ran the model across a range of dose frequencies as part of a BFRA. For a single behavioural dose initiated at time $t = 0$, the integral of the hedonic compartment over time, $H_{a,b}(t)_{single}$, can be calculated; this represents the sum of mood scores produced by the behaviour over the time of the simulation $t_{sim}$, and indicates whether the behaviour had a net positive or negative hedonic effect on the individual:

$$7) \int_0^{t_{sim}} H_{a,b}(t)_{single}\, dt = \int_0^{t_{sim}} \left( \frac{k_{a,pd} a_{pd}(t) - k_{b,pd} b_{pd}(t) - \frac{dH_{a,b}(t)}{dt}}{k_H} \right) dt$$

If multiple behavioural doses are added at a constant frequency, the opponent processes can be summed to find the total integral for $H_{a,b}(t)_{total}$:

$$8) \int_0^{t_{sim}} H_{a,b}(t)_{total}\, dt = \sum_{i=0}^{n} \int_{i/f}^{t_{sim}} \left( \frac{k_{a,pd} a_{pd,i}(t) - k_{b,pd} b_{pd,i}(t) - \frac{dH_{a,b,i}(t)}{dt}}{k_H} \right) dt$$

where $n$ is the number of behavioural doses added to the initial dose at a frequency $f$ during $t_{sim}$; therefore $i/f$ is the infusion start time of the new behavioural dose $i$. A Bode magnitude plot can then be plotted to show the system's frequency response, in terms of the magnitude of $\int_0^{t_{sim}} H_{a,b}(t)_{total}\, dt$ as a function of $f$. Unlike a typical Bode plot, since the opponent process is not a sinusoidal function, phase does not require analysis.

Allostasis occurs when the b-processes accumulate without sufficient recovery time. Hence, the simplest (and most plausible) way to change the rate of allostasis was to modify the Hill equation for the b-process, particularly $EC_{50_b}$ and $E_{\max_b}$ which have been associated with tolerance development in drug addiction (Luhmann & Intelisano, 2018; Maxwell, 2012). To simplify the model, I only modified $EC_{50_b}$ to simulate a change in moral incongruence, which in turn adjusted the rate of allostasis.

## *Results*

### Initial Model

Figure 10 shows the compartment values for $a_{pk}, b_{pk}, a_{pd}, b_{pd}$ and $H_{a,b}$ at a dose frequency of 0.006 min$^{-1}$, for $k_{Dose} = 10, k_{a,pk} = 0.02, k_{b,pk} = 0.004, k_{a,pd} = 1, k_{b,pd} = 1, k_H = 1, E_{0_a} = 0, E_{max_a} = 1, EC_{50_a} = 1, \gamma_a = 2, E_{0_b} = 0, E_{max_b} = 1, EC_{50_b} = 3$ and $\gamma_b = 2$.

Dose infusion time was set to 1 minute, while $t_{sim}$ was set to 1000 minutes. Since $EC_{50_b} > EC_{50_a}$, the biophase curve is shifted to the right for the b-process (Figure 10b), which results in a net positive score for $\int_0^{t_{sim}} H_{a,b}(t)_{single}\, dt$, since the a-process is greater than the b-process. However, at higher dose frequencies, $\int_0^{t_{sim}} H_{a,b}(t)_{total}\, dt$ has a net *negative* score, because the a-processes recover rapidly to baseline levels between behavioural doses, while the summed b-processes don't have time to recover due to the longer b-process decay time. In other words, opponent processes are generated at time intervals shorter than the critical decay duration of the b-process, but longer than the critical decay duration of the a-process (Solomon, 1980). This leads to a decreased set point and allostasis. The difference in decay rates can be observed in Figure 10c, which demonstrates buildup for the b-process but not for the a-process. Consequently, allostasis is observed in Figure 10d.

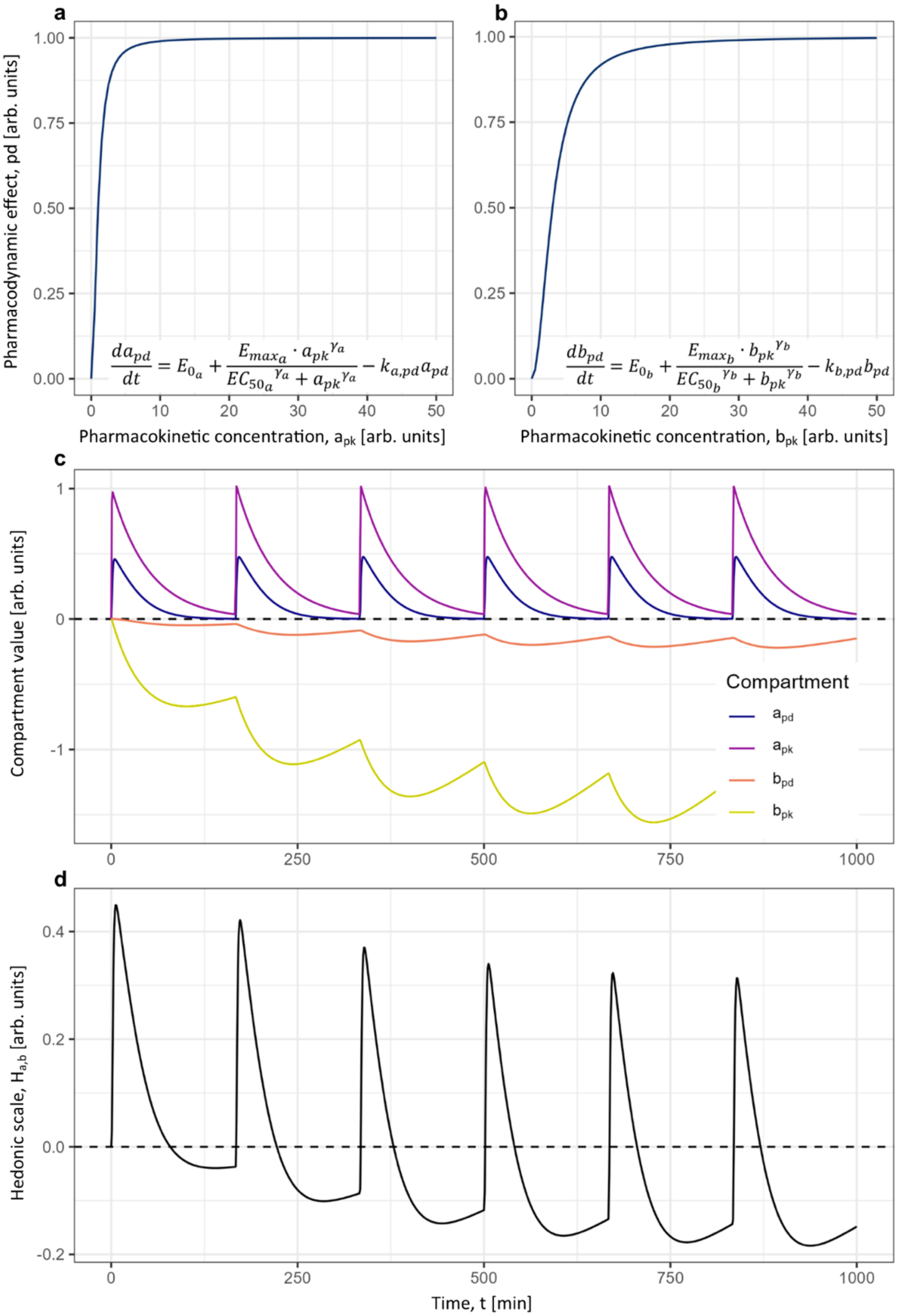


*Figure 10: Model showing how summed a- and b-processes can generate an overall decrease in mood (allostasis) over time at high dose frequencies. Subplot a/b: biophase graphs based on Hill equation parameters. Subplot c: mrgsolve-simulated compartment values for $a_{pk}, b_{pk}, a_{pd}$ and $b_{pd}$. Subplot d: simulated compartment values for $H_{a,b}(t)_{total}$, showing allostasis and reduced average mood over time.*

**Observing Hormesis via BFRA**

Figure 11 shows how the three dose-response models (hormesis, LNT, and LWT) in Figure 6 can be produced using a BFRA. I set $t_{sim}$ to 4000 minutes to allow the mrgsolve simulations (Figure 11c and d) to reach steady-state before calculating their integrals. The moderating effect of moral incongruence on the b-process was simulated by reducing $EC_{50_b}$ in the Hill equation, in effect treating mechanisms that reduce guilt as a reversibly competitive antagonist on the b-process (Maxwell, 2012). Put simply, reducing $EC_{50_b}$ increased the subject's moral incongruence (their feelings of guilt about the behaviour), which in turn increased the magnitude of the b-process and raised the rate of allostasis, leading to a more intense hedonic depression. (The darker the curve in Figure 11, the lower the value of $EC_{50_b}$.) Similar results can also be achieved by changing $E_{max_b}$ (simulating irreversible antagonism) or $\gamma_b$ (simulating a change in dose sensitivity) (Luhmann & Intelisano, 2018; Maxwell, 2012).

BFRA curves for different levels of moral incongruence can be seen in the graph of $\int_0^{t_{sim}} H_{a,b}(t)_{total}\, dt$ (Figure 11e) for varying levels of $EC_{50_b}$. Lower values of $EC_{50_b}$ shift the biophase curve to the left and generate a larger b-process. This increases the rate of allostasis, which becomes visibly observable in the mrgsolve simulation (Figure 11c-d) at dose frequencies of 0.001 $min^{-1}$ or greater. Higher values of $EC_{50_b}$ lead to higher hormetic thresholds (i.e., the $x$-intercept of the curve shifts to the right). This indicates that subjects with less moral incongruence are protected against allostasis over a greater range of behavioural frequencies. Put simply, *they can perform the behaviour more frequently without experiencing excessive guilt or depression.*

I used the graph of BFRA curves in Figure 11e to quantify the healthy limits of the digital behaviour for each level of $EC_{50_b}$:

- When $EC_{50_b}$ = 3.6, hormesis was observed in the BFRA curve. The behaviour could be performed without adverse effects at frequencies below approximately 0.0042 $min^{-1}$ (the hormetic threshold, or NOAEL). Above this frequency, negative total hedonic scores were observed.
- When $EC_{50_b}$ = 3.0, hormesis was observed but the hormetic threshold was lower at approximately 0.0026 $min^{-1}$.
- When $EC_{50_b}$ = 2.4, the BFRA curve was similar to the LWT model in Figure 6 (despite some non-linearity). The behaviour could still be performed up to a frequency of approximately 0.0008 $min^{-1}$ before adverse effects were observed.
- When $EC_{50_b}$ = 1.8, performing the behaviour at any frequency led to adverse effects. This is similar to the LNT model in Figure 6 (despite some non-linearity).

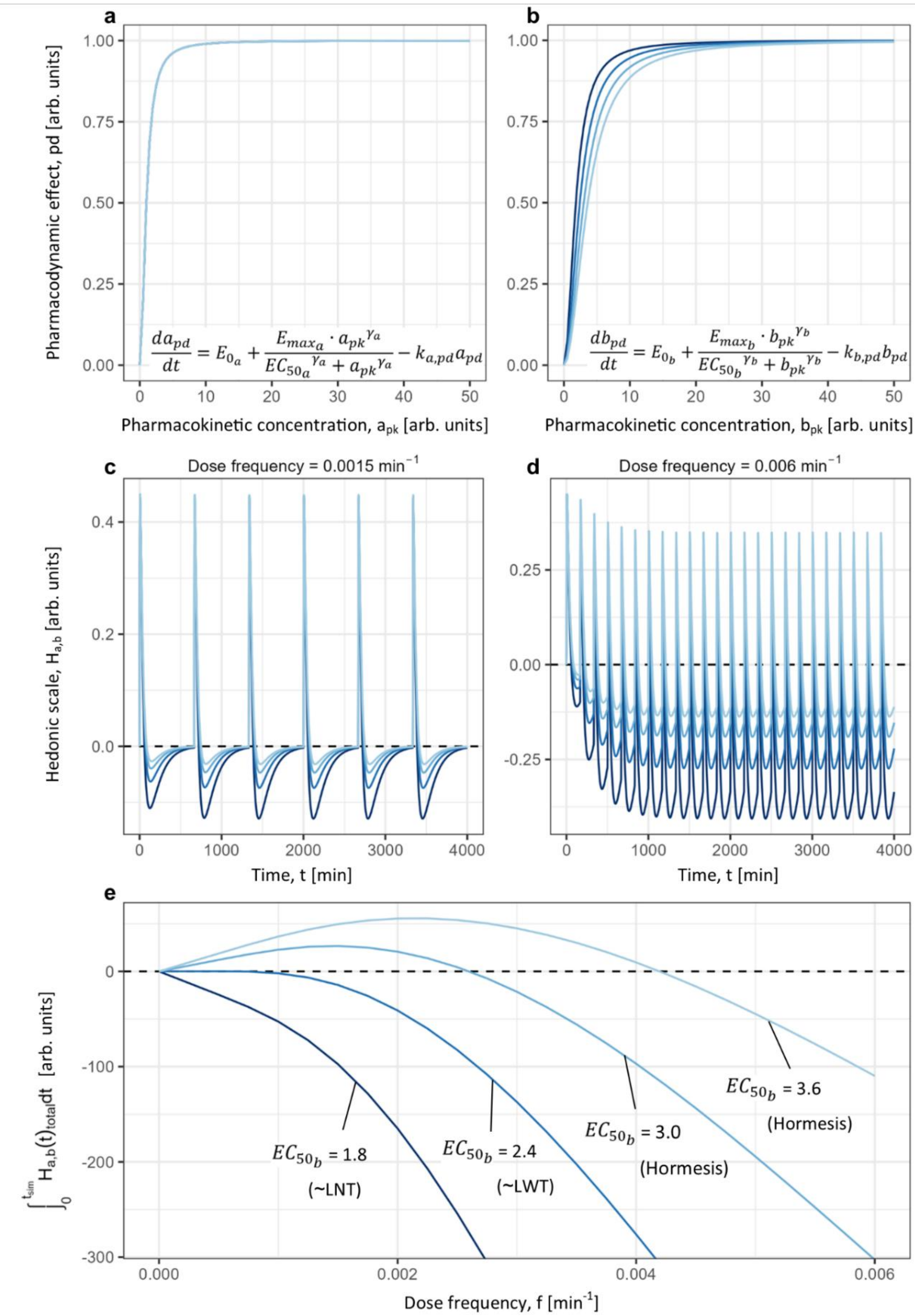


*Figure 11: Simulation for varying levels of $EC_{50_b}$ (shades of blue), representing different levels of moral incongruence. Subplot a/b: Biophase curves for a- and b-processes. Subplot c/d: $H_{a,b}(t)_{total}$ scores generated by mrgsolve. At a dose frequency of 0.0015 min$^{-1}$, b-processes decay to homeostatic levels, but at a dose frequency of 0.006 min$^{-1}$, allostasis is observed at all levels of $EC_{50_b}$. Subplot e: BFRA curves plotted as a function of dose frequency at each level of $EC_{50_b}$.*

We can apply this model to a hypothetical real-life scenario. Imagine that a person with a moral incongruence score of $EC_{50_b}$ = 3.0 performs the behaviour at a frequency greater than 0.0026 min$^{-1}$ (thus exceeding the hormetic threshold). Therefore, the person performs the behaviour excessively despite experiencing overall adverse hedonic effects, providing evidence of salience and mood modification. The graphs in Figure 11c and d also demonstrate allostasis beyond the hormetic threshold, providing evidence of tolerance and withdrawal. This suggests that the person may be addicted to the behaviour, based on Griffiths' six component model of addiction (M. Griffiths, 2005). However, further examination would be required to confirm that the remaining two components (conflict and relapse) are also present.

**Simulating the 'Standard Pattern of Affective Dynamics'**

Previous simulations incorporated low dose frequencies to leave substantive breaks between doses. This approach was suitable for modelling behaviours with short a-processes and refractory periods, such as orgasm during pornography use. However, I wanted to see what would happen if the behaviour were performed continuously for an extended period. Such a model could be applied to behaviours of longer duration, such as Internet, smartphone, or gaming sessions that last for hours. To do this, I increased the dose frequency to 0.2 min$^{-1}$ (one dose infusion every five minutes) to simulate near-continuous behavioural dosing. At this frequency, the a-processes from each individual opponent process didn't have time to fully decay to baseline, and the individual opponent processes appeared to merge into a single dynamic process. Remarkably, I observed that at this dose rate, the graph of $H_{a,b}(t)$ closely resembled Solomon & Corbit's 'standard pattern of affective dynamics' (Figure 1 of Solomon & Corbit, 1974), though on a timescale of minutes rather than seconds.

In Figure 12, I demonstrate a simulation of the standard pattern of affective dynamics (dark red, approximating Figure 5 of Solomon & Corbit, 1974), as well as the pattern of affective dynamics with tolerance induced by repeated stimulations (light red, approximating Figure 6 of Solomon & Corbit, 1974). For both graphs, I set $EC_{50_a}$ to 3 and $EC_{50_b}$ to 35 to reduce the b-process magnitude relative to the a-process. For the standard pattern, I set $k_{a,pk}$ to 0.02 and $k_{b,pk}$ to 0.005, while for the tolerance-induced pattern, I set $k_{a,pk}$ to 0.04 and $k_{b,pk}$ to 0.004, increasing the decay rate of the a-process and decreasing the decay rate of the b-process. Dose inputs were ended after 300 consecutive doses to observe withdrawal effects. As behavioural frequency increased, the hedonic state converged to an equilibrium value before the dose was withdrawn (Figure 12d). Five distinct phases are observed in both graphs, which can now be explained as follows:

1) The peak of the primary affective reaction (A-state): represents the cumulative effects of the a-processes from each behavioural dose.
2) Adaptation phase (A-state): the effects of cumulative b-processes appear while the a-processes start to recover to baseline levels.
3) Steady-state (A-state): equilibrium is reached, with a- and b-processes generating and recovering at equal rates.
4) The peak of the affective after-reaction (B-state): following removal of the stimulus, the a-processes are first to recover, while the b-processes take longer to decay, leading to a rapid decrease in hedonic scores. The subject is likely to feel strong withdrawal symptoms during this time.
5) Decay of after-reaction (B-state): finally, the b-processes recover to baseline.

These results suggest that the standard pattern of dynamics, as described by Solomon and Corbit (1974), may be comprised of the sum of multiple opponent processes, with short, intense a-processes followed by longer, less intense b-processes. However, further experimentation is necessary to confirm this hypothesis.

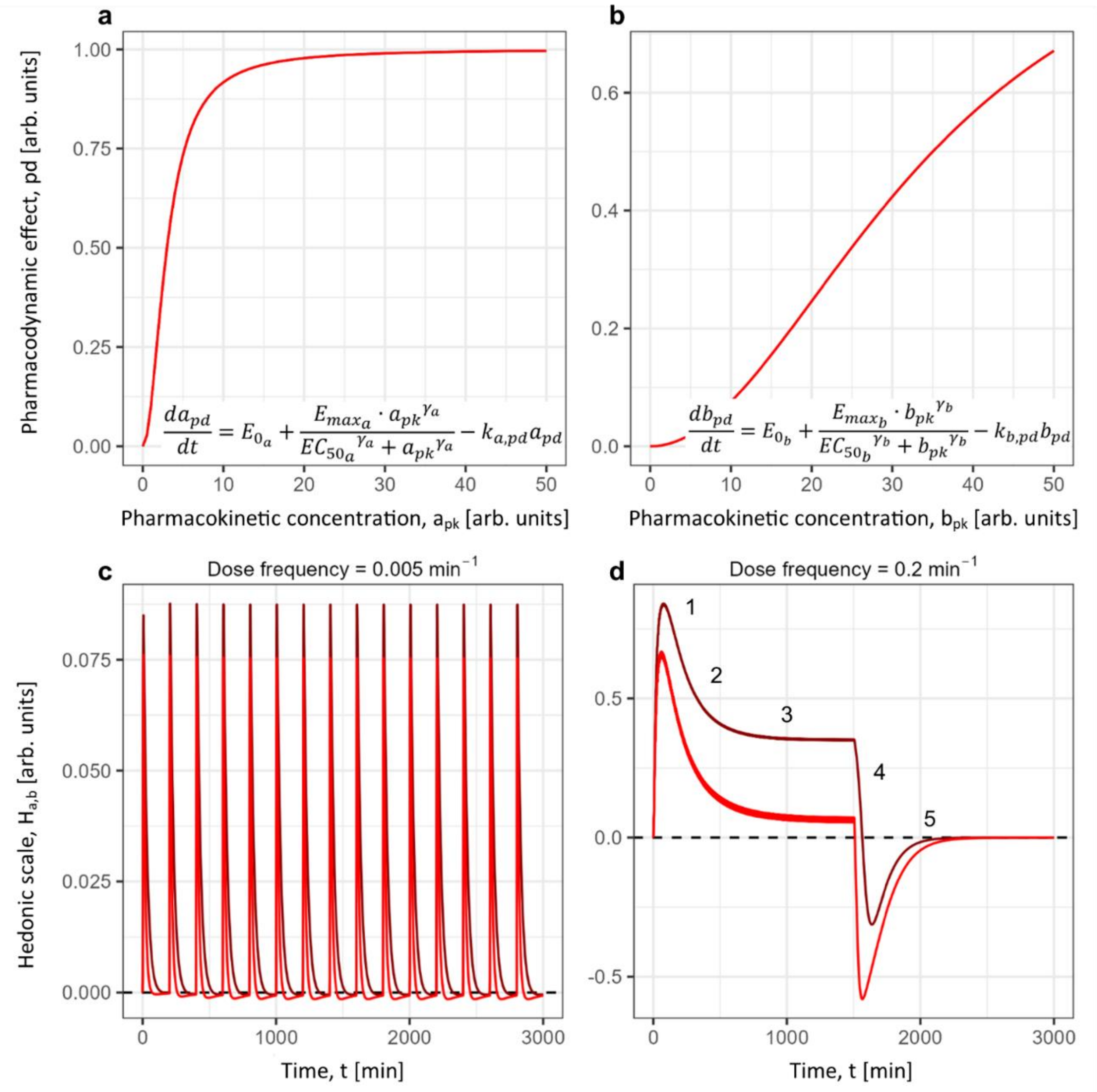


*Figure 12: Simulation of Solomon & Corbit's 'standard pattern of affective dynamics' (dark red;* $EC_{50_a}$ *= 3,* $EC_{50_b}$ *= 35,* $k_{a,pk}$ *= 0.02,* $k_{b,pk}$ *= 0.005), and tolerance-induced affective dynamics (light red;* $EC_{50_a}$ *= 3,* $EC_{50_b}$ *= 35,* $k_{a,pk}$ *= 0.04,* $k_{b,pk}$ *= 0.004). At a dose frequency of 0.2 min*$^{-1}$ *(near-continuous dose), the individual opponent processes appear to merge into a single dynamic process, and the graph of* $H_{a,b}(t)$ *(subplot d) demonstrates the following distinctive features of affective dynamics: peak of primary affective reaction (1), adaptation phase (2), steady-state (3), peak of affective after-reaction (4), and decay of after-reaction (5).*

## *Discussion*

### Implications of Behavioural Posology

Behavioural posology is a modelling paradigm that can be used for analysing the cumulative effects of behaviours delivered at varying frequencies, using BFRA. Coupled with empirical data, this approach may enable researchers to accurately predict the effects of performing addictive or compulsive behaviours at different frequencies, particularly those involving digital technologies. It also provides a way to quantify the healthy limits of a behaviour for an individual, which in turn can be used as one of the criteria for testing whether the individual is addicted to the behaviour. This has several clinical implications. For example, behavioural posology could help clinicians treat depressed patients by identifying and limiting problematic behaviours that have exceeded the hormetic threshold. However, to achieve this, experimental studies will be needed to quantify the parameters of the a- and b-processes of those behaviours so they can be simulated accurately. Future research in this field could also impact the design of ethical technologies by allowing guidelines to be set for healthy behavioural frequencies, enabling software creators to make more ethical design choices for their apps.

This article also presents four main findings:

1) The results support Koob & Le Moal's (2001) extension of Solomon & Corbit's (1974) model of allostasis by simulating it with an open-loop PK/PD model of opponent processes.
2) One can change the parameters of the model to replicate Solomon & Corbit's 'standard pattern of affective dynamics' (Solomon & Corbit, 1974), showing that it can be modelled as the sum of high-frequency, short-duration opponent processes.
3) One can also identify behavioural hormesis by altering the *frequency* of behaviour-induced opponent processes and observing the overall impact on the subject, rather than simply studying the effects of a single behavioural dose at different potencies.
4) The width of the hormetic region – i.e., the range of behavioural frequencies that produce a net positive hedonic effect – can be moderated by adjusting the parameters of the PK/PD model, particularly those linked to the b-process.

The PK/PD model has important implications for treating conditions such as depression. For patients who feel guilty about problematic behaviours, reducing the frequency of these behaviours and managing moral incongruence may be key to their treatment. Acceptance and commitment therapy can be a practical approach for these cases, as it helps patients to acknowledge negative thoughts and emotions related to their behaviour and make changes that align with their values (Hayes et al., 2006). Acceptance and commitment therapy has already shown promise for treating PPU in multiple studies (Crosby & Twohig, 2016; Grubbs, Perry, et al., 2019a; Sniewski et al., 2018; Twohig & Crosby, 2010). The PK/PD model presented here could be used alongside acceptance and commitment therapy to determine the healthy limits of these behaviours and assist clinicians in setting goals for their patients.

### Modifying the Model

Thanks to their grounding in neuropharmacological principles, PK/PD models have significant potential for accurately predicting behavioural effects. Here, I have created a simple PK/PD model that can be used as a base model for simulating any behaviour with opponent process dynamics. Readers are encouraged to download and modify the R code provided on the Open Science Framework website at https://osf.io/sau4v/ (N. Henry, 2023) to simulate other behaviours; this is as straightforward as running the function 'bode_plot()' and adjusting the input parameters. Examples of this are provided within the script for the reader's convenience. The mrgsolve package is flexible enough to allow for a wide range of customizations, and researchers can estimate parameters empirically to create accurate models for their own field of study.

For example, in the Figure 12 simulation, tolerance to the behavioural stimulus was simulated by increasing $k_{a,pk}$ (shortening the a-process) and decreasing $k_{b,pk}$ (lengthening the b-process). However, other adjustments were also tested to obtain similar results. For instance, increasing $EC_{50_a}$ (simulating the development of tolerance via a competitive agonist) lowers both the peak of the primary affective reaction and steady-state value, and increases the magnitude of the affective after-reaction. Alternatively, reducing $E_{max_a}$ produces similar effects, as does modifying the clearance rates of the pharmacodynamic compartments ($k_{a,pd}, k_{b,pd}, k_H$). (Note that to achieve a positive steady-state, the a-process magnitude needs to exceed that of the b-process.)

To perform a true BFRA, it is important to keep $Dose_{individual\ session}$ constant for each simulation. However, future experiments should also consider the effects of changing the dose magnitude, perhaps as a function of tolerance development. By changing the ratio of a- and b-process magnitudes, one can easily adjust the rate of development of allostasis and apparent tolerance. If more sophisticated modification is required, one could add a parallel tolerance compartment to create a feedback loop, similar to those in control system models of addiction in the literature (e.g., Ahmed & Koob, 2005; Amigó et al., 2008; Bobashev et al., 2017; Chou & D'Orsogna, 2022; Dumas & Pollack, 2008; Gårdmark et al., 1999; Levy et al., 2013; Newlin et al., 2012; Peper, 2009b; Porchet et al., 1988; Upton & Mould, 2014; Zou et al., 2020). Several types of functional tolerance, both competitive and non-competitive, could be added, including both pharmacokinetic tolerance (such as changes in metabolite production or transporter function) and pharmacodynamic tolerance (such as modifications to receptor functionality or changes to signal pathways) (Dumas & Pollack, 2008).

### Experimental Validation of Behavioural PK/PD Models

If validated experimentally, this PK/PD model has the potential to explain the mechanisms behind the relationships between digital behaviours and mental health metrics. To validate this, longitudinal survey methods such as EMA (Shiffman & Stone, 1998), would be required to capture the temporal dynamics of specific behaviours. An EMA involves regularly sampling an individual's current state, typically by making a participant complete multiple smartphone-based surveys daily (de Vries et al., 2021). By fitting a PK/PD model to high-frequency EMA data, one could test the hypothesis that allostasis produced by opponent processes can predict mental health metrics relative to behaviour times. To test for hormesis, the Mack-Wolfe test, a non-parametric rank test for detecting 'umbrella' alternatives to monotonic functions, could be performed on the BFRA curves (Deng et al., 2000; Kim et al., 2016). In this way, future researchers may be able to use behavioural posology to hypothesise, model, and test mechanisms for behavioural addictions.

Our PK/PD model can be run across a range of dose frequencies to perform a BFRA, but only considers constant frequencies. It also focusses on short-term craving and withdrawal effects, which makes it useful only for prediction of hedonic states in the short- to medium-term. While this allows for a more accurate BFRA, it may limit the model's applicability to cases of long-term addiction with a bidirectional relationship between craving and behavioural frequency. Chou and D'Orsogna (Chou & D'Orsogna, 2022) offer a more comprehensive control-theoretic model of drug addiction by incorporating a craving feedback loop that can accurately simulate the progression to behavioural addiction. A similar feedback loop could be applied to the model, representing the buildup of neural memories that trigger craving and withdrawal symptoms in the long-term.

### Future Research

In this article, I focused on hedonic outcomes for a hypothetical digital behaviour, using moral incongruence as a moderator of the b-process. However, other moderators could be explored. For instance, one could measure anxiety outcomes due to pornography use as moderated by moral disapproval of pornography (Guidry et al., 2020), or measure stress outcomes due to social media use as moderated by job characteristics (Brooks & Califf, 2017). Furthermore, this type of modelling could be applied to several other fields, such as predicting emotional responses to stock market fluctuations and vice-versa (Bollen et al., 2011; Dhaoui & Bacha, 2017), predicting mood outcomes for different styles of music (Tuomas, 2009), or predicting marital stability based on positive and negative interactions between partners (Gottman et al., 1998). I encourage readers to consider whether a behavioural PK/PD model could be helpful in their field of study.

Another possibility lies in the similarity between the shape of the opponent processes modelled in this article (for example, in Figure 11), and the shape of a neuronal action potential. Specifically, an action potential could be characterised as an opponent process, with depolarization being the a-process and hyperpolarization the b-process. This raises the possibility that the affective states presented in this article could be modelled as the sum of action potentials firing simultaneously in adjacent neurons. Could it be that such an additive mechanism exists within the brain's reward centres? For example, could a person's hedonic state be modelled by the addition of membrane potentials, currents, or even firing rates of neurons within the ventral tegmental area (VTA), an area of the brain involved in reward? Electrode stimulation of brain regions such as the VTA is known to increase the firing rate of neurons in those regions, while simultaneously producing pleasurable hedonic states (Berridge & Kringelbach, 2015; Friedman et al., 2009; Olds, 1956; Olds & Milner, 1954; Solt et al., 2014). Other brain regions are also likely to play a role; for example, fMRI evidence suggests that the VTA is only indirectly linked to reward magnitude tracking, with neural population activity in the nucleus accumbens being a more reliable correlate of reward magnitude (Fiallos et al., 2017). Yet studies of neural firing within the VTA have shown a pattern in hyperpolarization-activated currents ($I_h$) where both a 'depolarizing voltage sag' and a 'repolarizing voltage sag' are observed; these patterns are qualitatively similar to that seen in Figure 12d (e.g., Biel et al., 2009; Chu et al., 2010; Huang et al., 2019; Momin et al., 2008). Future research should investigate whether this indicates a link between the high-frequency firing of action potentials in the brain's reward centres and the 'affective dynamics' model, as Figure 12d shows. Such research may improve our understanding of how people perceive hedonic states at a cellular level.

### *Conclusion*

Behavioural posology is a modelling paradigm that can be used to analyse the effects of repeatable behaviours on mental wellbeing, and to determine the healthy limits of such behaviours. In this article, I have demonstrated how behavioural posology can be used to model depression induced by repetition of a digital behaviour. The model may also provide a possible mechanism for frequency-based hormesis, in which low frequencies of a behaviour have some long-term hedonic benefits, but higher frequencies have negative effects on average. This has significant implications for the treatment of behavioural addictions, as it may help clinicians to set goals with greater precision for behaviour modification in their patients, in conjunction with a therapy such as acceptance and commitment therapy. Further research is needed to validate this model empirically across a range of behaviours, which may be achievable using smartphone-based Ecological Momentary Assessments. This article highlights the need for continued development of PK/PD models using the behavioural posology paradigm. It is my hope that future research in this space will enable us to better predict the healthy limits of behaviours for any individual.

## Chapter 6: The Impact of Pornography Use (IPU) Study

### Prelude

The theoretical approach of the behavioural posology study produced an opponent process model of pornography use that requires validation with real-world data. This model predicted several phenomena linked to repeated pornography use, such as the presence of a- and b-processes, allostasis, and tolerance buildup from high-frequency use. However, testing the accuracy of all components of this model would require multiple studies, far exceeding the scope of this thesis. As a result, I had to decide which aspect of the model was most critical to investigate.

One of the predictions of the 'behavioural addiction' model of pornography use is that people continue to use pornography and perform other sexual behaviours compulsively despite adverse effects and develop a tolerance; users then feel compelled to seek out more potent forms of pornography, or use pornography at a greater frequency, in order to experience the same level of sensation as before, or to counter withdrawal symptoms (Gola et al., 2017; Lewczuk, Wizła, et al., 2022). It is possible that such a mechanism may lead to hedonic depression, although more research is needed to determine whether repeated pornography use can induce tolerance or withdrawal effects. There is also a question of whether there is a healthy non-zero limit to pornography use – in other words, whether pornography use follows a hormetic or Linear With Threshold (LWT) model instead of a Linear No Threshold (LNT) model.

Regardless of whether pornography use can become addictive, impulsive, or compulsive, it is important to know where the healthy limit of this behaviour is for each individual in order to provide effective treatment recommendations. Yet quantifying this healthy limit for each person is challenging without an accurate model of temporal dynamics associated with the behaviour. If validated with empirical data, the opponent process model may offer valuable insights into the nature of these temporal dynamics. So, as a first step in testing the model, I needed to validate the existence of opponent process dynamics associated with pornography use.

Hence, my main goal in the Internet Pornography Use (IPU) study was to test for the existence of a b-process following pornography use as a first step in validating the opponent process model of pornography use. In turn, the data from this study could also be used to improve our understanding of the directionality between pornography use and associated mental health outcomes and, hopefully, provide a better model for quantifying the No Adverse Effect Level (NOAEL) of pornography use for each individual, based on their level of moral incongruence. It may also allow us to discover a mechanism that explains how the interaction between pornography use and moral incongruence may contribute to mental health disorders such as depression.

The IPU study described in this Chapter was designed to gather quantitative longitudinal data from pornography users to validate aspects of the opponent process model described in Chapter 5. To test whether the b-process exists for pornography use, I chose to implement an 'affective chronometry' approach, in which an EMA was performed to measure participants' temporal dynamics in relationship to their sexual activities.

***Manuscript***

The manuscript resulting from this Chapter has been submitted to the journal 'Archives of Sexual Behaviour'[5], and is uploaded as a preprint to Research Square.

Henry, N. I. N., Pedersen, M., Williams, M., & Donkin, L. (2024). Quantifying the Affective Dynamics of Pornography Use and Masturbation: An Ecological Momentary Assessment Study. *Research Square preprint.* https://doi.org/10.21203/rs.3.rs-5094782/v1

 Minor grammatical adjustments have been made to ensure consistency with the remaining thesis.

[5] https://creativecommons.org/licenses/by/4.0/

## Quantifying the Temporal Dynamics of Pornography Use and Masturbation: An Ecological Momentary Assessment Study

### *Abstract*

The relationships between pornography use, masturbation, moral incongruence, and mental health are poorly understood. While the link between problematic pornography use (PPU) and depression is well documented, the temporal dynamics (i.e., fluctuations in mental health states over time) associated with pornography use and masturbation have not yet been quantified. Utilizing an Ecological Momentary Assessment (EMA) design, I measured the temporal dynamics of mental health variables collected from 22 participants before, during and after pornography use and masturbation, and examined the moderating role of moral incongruence in these relationships. Participants completed an initial survey followed by a four-week EMA, capturing data on sexual activities and mental health variables. Bayesian hierarchical mixed-effects models were employed to analyse temporal dynamics. Findings suggest that pornography use and masturbation were linked to changes in affective states that spiked both before and after sexual episodes. The magnitude of these state changes was greater in participants with high moral incongruence, who experienced increases in guilt, shame, loneliness, and difficulty thinking, along with decreased hedonic mood and perception of relationship connectedness, either before or after sexual episodes. These findings signalled the potential for intermittent spiking effects in craving prior to sexual episodes, as well as potential evidence for 'brain fog' following pornography use in both low and high moral incongruence participants. Further, I discovered opponent process dynamics in the mood of high moral incongruence participants, providing a plausible mechanism by which PPU may lead to depression.

### *Introduction*

#### Problematic Pornography Use

Problematic pornography use (PPU) is characterised by a pattern of pornography consumption that causes distress and functional impairment across personal, social, or occupational areas, and is marked by an inability to control pornography use despite these adverse effects (Bőthe, Nagy, et al., 2024; Ince et al., 2021). PPU has only recently been clinically recognised as an impulse-control disorder, having been added as a subcategory of Compulsive Sexual Behaviour Disorder (CSBD) in the 11th edition of the International Classification of Diseases (ICD-11) (Kraus et al., 2018). Yet despite this recognition, there remains controversy over whether PPU should be classified as an addiction (Bőthe, Potenza, et al., 2024; Brand et al., 2020; Pistre et al., 2023). While compulsive pornography use can have psychosocial consequences, PPU has features overlapping both behavioural addictions and impulse-control disorders, and as such may have a distinct symptomology from true addiction (Grubbs, Perry, et al., 2019a; Ravish et al., 2024). Despite a lack of professional consensus, there remains a high prevalence of anecdotal evidence for self-perceived 'pornography addiction' in popular culture and online discourse.

Prior research has linked PPU to depressed mood, decreased relationship connectedness (Cardoso et al., 2023; Lambert et al., 2012; Maitland & Neilson, 2023; Mestre-Bach & Potenza, 2023a; Vaillancourt-Morel et al., 2024), increased anxiety, guilt, shame, loneliness, difficulty thinking, and suicidal thoughts (Cardoso et al., 2023; Fernandez et al., 2021b; Guidry et al., 2020; Maitland & Neilson, 2023; McGraw et al., 2024; Mestre-Bach & Potenza, 2023a), and to other psychosocial disorders (Chasioti & Binnie, 2021). Despite some evidence that pornography use can have a positive effect on attitudes towards sexuality (Mckee, 2007; Rissel et al., 2017), it has also been associated with lower relationship satisfaction and commitment, especially when pornography use occurs without the partner's consenting knowledge (Bechara et al., 2003; Floyd & Grubbs, 2022; Grubbs, Perry, et al., 2022; Kohut et al., 2017; Lambert et al., 2012; Perry, 2016; Vaillancourt-Morel et al., 2024; Willoughby & Dover, 2022; Wright et al., 2017; Zitzman & Butler, 2009). The literature also suggests that PPU can significantly affect the user's relationships with family, friends, and colleagues (Bridges & Morokoff, 2011; Fagan, 2009; Stack et al., 2004; Stewart & Szymanski, 2012). Hence, there are concerns over the societal and public health consequences of increasing consumption of pornographic material (Grubbs & Perry, 2019; Lambert et al., 2012).

One of the key factors predicting self-reported addiction to pornography use is moral incongruence – defined as the feeling of moral disapproval towards one's own use of pornography (Grubbs, Floyd, et al., 2022; Grubbs, Perry, et al., 2019a; Grubbs & Perry, 2019; Lewczuk et al., 2020; Perry, 2018a). A review by Floyd and Grubbs of the past 5 years of research has identified that moral incongruence serves as a moderating factor for various pornography-related issues, such as emotional distress, relationship difficulties, and self-perceived addiction (Floyd & Grubbs, 2022). Moral incongruence is influenced by multiple factors, including an individual's religious beliefs, cultural norms, conservative sexual values, apprehensions about sexual exploitation, and the potential impact on interpersonal relationships (Chen, Wang, et al., 2023; Hoagland et al., 2023; Ince et al., 2023; Lewczuk et al., 2021; Su et al., 2023). Despite these findings, the mechanisms behind the relationship between moral incongruence, pornography use, and mental health remains unclear.

Understanding the mechanisms linking pornography use and affective states is vital to clarify whether PPU is merely an impulse-control disorder, or a true addiction that has elements of impulsivity and compulsivity. It will also help to enhance identification of clinically relevant thresholds for PPU.

### Affective Chronometry

Many neuropsychological phenomena have a curvilinear decay, such as an exponential or power-law decrease, in response to a stimulus. Examples that unfold over several hours include memory retention (Candia et al., 2019; Kahana & Adler, 2017; Murre & Dros, 2015; Peterson & Peterson, 1959; Subirana et al., 2017; Wixted & Ebbesen, 1991) and emotional responses (D. J. Anderson & Adolphs, 2014; Botelho et al., 2018; Dejonckheere et al., 2020; Feidakis, 2011; Heller et al., 2015; Picard, 1997; Solomon & Corbit, 1974). These temporal dynamics can be measured using EMA, a longitudinal methodology that collects real-time participant data about their thoughts, feelings, or actions, often multiple times a day (Bos et al., 2015; Shiffman & Stone, 1998). This approach, more broadly known as 'affective chronometry,' tracks the timing of temporal dynamics (Botelho et al., 2018; Dejonckheere et al., 2020; Feidakis, 2011; Heller et al., 2015). For instance, Heller et al. (2015) used EMA to measure the decay of positive emotions after participants received different monetary rewards. Their findings indicated that participants' emotional reactions approximated an exponential decay process over time, with the initial amplitude and decay rate correlating with brain activity in functional magnetic resonance imaging (fMRI) scans. This decay pattern is thought to result from how substances move between body areas, such as hormones moving through neural and vascular compartments (Ibarra et al., 2020).

It is possible that curvilinear decay can be observed in individuals after engaging in pornography use or masturbation. By treating sexual activity as a stimulus that generates affective opponent processes in the body (N. Henry et al., 2023; Solomon & Corbit, 1974), I hypothesised that an EMA would allow us to observe and quantify both the emotional high during a sexual episode (the 'a-process'), and the negative emotional after-effects (the 'b-process')[6]. I also hypothesised that these after-effects would follow an exponential decay curve.

### Aims of the Present Study

The objectives were:

1. To model the temporal dynamics of pornography users in relation to sexual activity.

[6] For a more detailed explanation of this opponent process model, refer to Henry et al. (N. Henry et al., 2023).

2. To determine whether moral incongruence moderated the temporal dynamics produced by pornography use and masturbation.
3. To evaluate the feasibility of conducting an EMA assessment of pornography users, in preparation for a larger cohort of future participants.

### *Methods*

#### Study Overview

The study recruited participants through two methods: a pilot study at Auckland University of Technology, New Zealand, using flyers, followed by an exploratory study advertised on the r/pornfree subreddit, known for its anti-pornography stance (r/pornfree, 2022). The pilot study participants received $50 NZD gift vouchers, whereas the exploratory study participants volunteered without financial incentives due to funding limitations.

Ethics approval for both studies was provided by the Auckland University of Technology Ethics Committee (AUTEC). The pre-EMA survey was conducted on the online survey and database platform REDCap (Patridge & Bardyn, 2018), while the EMA was conducted on SEMA3 (Smartphone Ecological Momentary Assessment), an application for longitudinal survey research available on both iOS and Android (O'Brien et al., 2024). REDCap data were stored on a locally hosted, secure server on-site at AUT, with 128-bit encryption, daily backups, and two-factor authentication. Only authorized members of the research team and REDCap administrators had access to the project, with strict permissions applied to control access to identifiable data. Data collected via the SEMA3 app were encrypted and stored on secure University of Melbourne servers, accessible only to members of the research team and SEMA3 administrators. The platform used a Google Firebase backend, with Firebase Cloud Functions managing communication between app components. Participant data were anonymized using unique 9-digit identifiers linked to hashed emails for account verification. No personal identifiers were stored in the SEMA3 database; these were only accessed through the REDCap database to send koha to participants following the study. Participants were informed that they could request for their data to be deleted at any time.

The study was delivered in two parts: a pre-EMA survey for collecting demographic and descriptive variables, followed by a four-week EMA to monitor temporal dynamics in relation to sexual activity. The pilot study participants also answered a post-EMA survey regarding their EMA experience. Despite different recruitment phases, the core survey questions were consistent between the two studies, allowing me to combine the pilot study data with the exploratory study data for the final analysis. However, the main purpose of the pilot study was to test our methodology, whereas the primary goal of the exploratory study was data collection and analysis using the validated protocol.

**Participants**

Inclusion criteria were proficiency in English; regular Internet access and a compatible smartphone; use of pornography at least once in the past month; and minimum age of 18. There was no a priori constraint on sample size. I used Wilcoxon's rank sum test and Fisher's exact test to compare demographic frequencies between the low and high moral incongruence groups; no significant difference in demographic makeup was detected for any variable.

**Pre-EMA Measures**

The pre-EMA survey, conducted on REDCap, containedthe following measures.

***Demographics and Pre-Screening.*** Participants were asked generic demographic questions about age, gender, ethnicity, highest level of schooling, employment, relationship status, and religiosity. For screening purposes and to determine baseline sexual activities, participants were asked to state their frequency of pornography use, masturbation, and sexual intercourse over the past month. They were also asked questions regarding the use of any applications or membership in groups aimed at reducing pornography use or masturbation, such as online 'Reboot' groups.

***Moral Incongruence and Pornography Consumption.*** Participants were asked to identify their level of moral incongruence related to masturbation with pornography use, masturbation without pornography use, and pornography use without masturbation. These were measured with one item each (e.g., "I believe that pornography use is morally wrong") on a scale of 0 (not at all) to 6 (very strongly) based on similar measures in prior studies (Grubbs, Exline, et al., 2015; Grubbs, Kraus, et al., 2019; Lewczuk et al., 2020). Typical pornography use levels and PPU screening was performed with the six-item Problematic Pornography Consumption Scale (PPCS-6) (Bőthe, Tóth-Király, Demetrovics, et al., 2020, p. 6).

***Baseline Mental Health Variables.*** Anxiety and depression disorders were screened with the Hospital Anxiety and Depression Scale (HADS) (Snaith, 2003; Spinhoven et al., 1997). A subset of questions from the Multidimensional Fatigue Inventory (MFI) was used to measure typical levels of mental and motivational fatigue (Smets et al., 1995). Trait levels of guilt and shame proneness were assessed with the eight-item Guilt and Shame Experience Scale (GSES) (Maliňáková et al., 2019). Typical levels of loneliness were assessed with the eight-item short-form UCLA Loneliness Scale (ULS-8) (Hays & DiMatteo, 1987). Participants in a relationship were asked a subset of the seven-item relationship assessment scale to measure relationship connectedness and sexual satisfaction within the relationship (Bőthe, Tóth-Király, Demetrovics, et al., 2017; Hendrick et al., 1998). Participants' social desirability rating, which may indicate biased responses, was assessed with the Brief Social Desirability Scale (BSDS) (Haghighat, 2007).

**EMA Procedure**

EMA data was collected using SEMA3. Participants engaged in a four-week program, responding to five daily surveys, each lasting 1-2 minutes with a 3-hour response window. Notifications were sent at 9 am, 12 pm, 3 pm, 6 pm, and 9 pm. These surveys were designed to assess participants' mental health in the moment on a 0-10 scale. For example, mood was measured on a bidirectional scale capturing both positive and negative valence ("On a scale of 0-10, what is your CURRENT mood? 0 = extremely unhappy, 5 = neutral, 10 = extremely happy)"), while anxiety was measured with a unipolar scale reflecting only negative valence ("On a scale of 0-10, how anxious do you CURRENTLY feel? 0 = no anxiety, 5 = moderate anxiety, 10 = extremely high anxiety"). Variables measured were mood, anxiety, guilt regarding sexual activity, shame regarding sexual activity, loneliness, difficulty thinking, relationship connectedness, and cravings related to pornography or sexual behaviour. Further details on these measures can be found in the online Appendices.

Additionally, participants were asked to complete a 2–3-minute survey immediately following any episode of sexual intercourse, masturbation, or pornography use[7]. They were again asked to rate their mental health scores in the current moment, along with questions about the type, intensity, and duration of their sexual episode, including their highest level of mood during the episode (using an identical scale to the 'mood' variable). They were also asked to categorise their episode as one of the following: sexual intercourse with partner(s), pornography use only, masturbation only, pornography use with masturbation only, pornography use with masturbation and orgasm, or masturbation with orgasm only. Finally, they were asked an open-ended question about the triggers that led to their episode, such as: 'What were the events or triggers that led to you using pornography?', with responses subject to a qualitative content analysis. Participants were informed that their data would be kept confidential within the research team.

[7] The post-episode survey was self-initiated. However, each time participants opened the SEMA3 app (either for the post-episode survey or for the scheduled surveys), they were presented with both survey types, with a reminder of when to complete each survey.

### Statistical Analysis

If an affective b-process occurs following pornography use, one would expect the amplitude of this b-process to spike immediately following the episode, before decaying gradually over time. In other words, the person would experience an emotional reaction to the pornography use that would gradually reduce in intensity. The rate at which this intensity changes would also be unlikely to be constant, especially if it involves neurohormonal decay processes. Therefore, I tested the hypothesis that following a sexual episode, temporal dynamics would approximate an exponential decay process of the form:

$$1) \quad w(t) = ae^{-bt} + c + \varepsilon$$

where $w(t)$ is the mental health variable, $t$ is time with the sexual episode occurring at $t = 0$, $a$ is the initial amplitude or effect size right after the sexual event, $b$ is the decay constant that governs how quickly the effect diminishes, $c$ is the subject's baseline level of the mental health variable, and $\varepsilon$ is random noise. Similarly, I tested the hypothesis that prior to a sexual episode, temporal dynamics would approximate an exponential growth process of the form:

$$2) \quad w(t) = ae^{bt} + c + \varepsilon$$

which, when plotted, is the mirror image of Equation 1) around the axis at $t = 0$. This allowed me to detect any increases in the mental health variable prior to sexual episodes.

As the null hypothesis, I also fitted a linear steady-state model to both pre- and post-episode data of the form:

$$3) \quad w(t) = d + \varepsilon$$

where $d$ is the average mental health score, indicating a steady state unaffected by the sexual event.

I used the time stamps of EMA responses to measure temporal dynamics in an approach similar to that of disease progression modelling (e.g., see Raket, 2020, 2020/2022). This allowed me to model each mental health variable as a function of time and type of sexual episode, resulting in a dataset comprised of mental health data both pre- and post-episode, with each sexual episode aggregated at time $t = 0$. However, in cases where mental health scores were measured between sexual episodes, data could be considered both 'post-episode' and 'pre-episode', which could lead to possible cross-contamination. To control for this, I assessed the impact of creating models using both truncated and non-truncated datasets. Truncation in this case refers to exclusion of data that was closer to another sexual episode than the one being examined, thus reducing the confounding influence of the farther episode. For example, take a participant who had two sexual episodes eight hours apart, and completed three EMA surveys during this time, where two of those surveys were performed closer to the first sexual episode. For the truncated analysis of the first sexual episode, only data from the first two surveys would be analysed relative to that episode, while the third survey would be excluded.

A Bayesian hierarchical mixed-effects model was employed to account for individual differences, with random intercepts across participants. This approach allowed me to model the individual variability in temporal dynamics while estimating overall population-level effects. I used the brms package in R v4.3.0 for Bayesian modelling of the data (Bürkner, 2017; R Core Team, 2022). In lieu of traditional p-values, I employed Bayes Factors (BFs) to gauge the strength of evidence for competing hypotheses, providing evidence for the most appropriate model given the observed data (Kruschke & Liddell, 2018; Michailovs et al., 2024). BFs ranging from 3 to 5 denote ‘weak’ evidence, while 5 to 10 suggests ‘moderate’ evidence, 10 to 100 represents ‘strong’ evidence, and greater than 100 is ‘very strong evidence’ (Etz & Vandekerckhove, 2016). I reported $BF_{10}$ when evidence favoured the alternate hypothesis that the model was exponential, and $BF_{01}$ when evidence favoured the null hypothesis of no effect. Additionally, 95% credible intervals were provided to convey the uncertainty in each estimate (Wagenmakers et al., 2018).

The following bounded priors were specified for each parameter: uniform priors for $a$ (-10 to 10, to cover the entire possible range of initial effect sizes), $b$ (-10 to 0 for the decay model, and 0 to 10 for the growth model, representing a half-life ranging from approximately 5 minutes to infinity), and $c$ (0 to 10 to cover all possible mental health scores). For the null hypothesis (no effect), I used normally distributed priors for $d$ with mean and variance taken from the mental health variable being measured.

To test for differences in temporal dynamics between participants with low and high moral incongruence, I calculated the difference between each participant's affect scores within 12 hours both leading up to and following sexual episodes and the mean of their affect scores from more than 12 hours before or after sexual episodes[8]. This difference provided an approximate measure of the impact of sexual activity on affect scores following the sexual episode, as well as a measure of craving and withdrawal effects leading up to the sexual episode. I then compared

[8] This threshold was chosen because in most cases, the exponential models decayed to near baseline within 12 hours.

these measures between the low and high moral incongruence groups using the BayesFactor package in R to perform Bayesian t-testing (Morey & Rouder, 2012).

***Results***

### Descriptive Statistics and Demographics

In total, 3255 scheduled EMA surveys were delivered to participants, of which 2175 contained participant responses. The pre-EMA survey was accessed by 91 participants, with 38 (41.8%) completing the entire survey. Of these, 7 (18.4%) were from the pilot study, from whom 6 contributed data to the EMA; while 31 (81.6%) participants were from the exploratory study, from whom 18 contributed data to the EMA. Of the participants who contributed to the EMA, 20 (90.9%) participants were male, and 16 (72.7%) participants were not in a relationship. Participants' demographic characteristics are presented in Table 1. Overall compliance rates were 25% for the pilot study, and 29% for the exploratory study. No face validity issues were identified (e.g., repetitive responses to Likert scale questions, or nonsensical inputs in open fields). Missing data was not imputed due to its temporal complexity.

The sample size was too small to analyse moral incongruence as a continuous variable, preventing any reliable assessment of its underlying statistical distribution. Hence, to facilitate group-level comparisons with maximum statistical power under these constraints, I performed a median split to compare the responses of participants with low moral incongruence (responses regarding moral incongruence due to masturbation with pornography use ranging from 0-3) and high moral incongruence (range 4-6).

*Table 1: Demographic data from pre-EMA survey for 22 participants who contributed data to the final EMA. Participants were divided by level of moral incongruence with respect to pornography use with masturbation, using a median split. Additional descriptive statistics from the pre-EMA survey can be found in Appendix A.*

| Variable | High moral incongruence, N = 10 | Low moral incongruence, N = 12 |
|---|---|---|
| Age (years) | 27.30 (11.19) | 29.50 (6.68) |
| Gender | | |
| Woman | 0 (0%) | 2 (17%) |
| Man | 10 (100%) | 10 (83%) |
| Gender diverse | 0 (0%) | 0 (0%) |
| Prefer not to say | 0 (0%) | 0 (0%) |
| Ethnicity | | |
| NZ European | 0 (0%) | 3 (18%) |
| Chinese | 0 (0%) | 1 (6%) |
| Indian | 3 (18%) | 0 (0%) |

| Variable | High moral incongruence, N = 10 | Low moral incongruence, N = 12 |
|---|---|---|
| English | 2 (12%) | 2 (12%) |
| European/North American Caucasian | 7 (41%) | 4 (24%) |
| Middle Eastern | 1 (6%) | 1 (6%) |
| Hispanic/Latin American | 1 (6%) | 3 (18%) |
| African | 0 (0%) | 0 (0%) |
| Other/unspecified | 3 (18%) | 3 (18%) |
| Sexual orientation | | |
| Heterosexual | 10 (100%) | 5 (42%) |
| Bisexual | 0 (0%) | 5 (42%) |
| Homosexual | 0 (0%) | 1 (8.3%) |
| Asexual | 0 (0%) | 0 (0%) |
| Unsure | 0 (0%) | 1 (8.3%) |
| Prefer not to say | 0 (0%) | 0 (0%) |
| Currently in long-term relationship | | |
| Yes - I have been with my current partner for at least 1 year | 1 (10%) | 3 (25%) |
| Yes - I have been with my current partner for less than a year | 2 (20%) | 0 (0%) |
| No - I do not have a partner currently | 7 (70%) | 9 (75%) |
| Prefer not to say | 0 (0%) | 0 (0%) |
| Importance of religion in life | | |
| Not at all important | 1 (10%) | 8 (67%) |
| Not too important | 2 (20%) | 3 (25%) |
| Somewhat important | 4 (40%) | 1 (8.3%) |
| Very important | 3 (30%) | 0 (0%) |
| Primary religion | | |
| Catholic (including Roman Catholic and Orthodox) | 5 (50%) | 2 (17%) |
| Protestant (e.g. Anglican, Orthodox, Baptist, Lutheran, United Church of Canada) | 1 (10%) | 1 (8.3%) |
| Christian Orthodox | 1 (10%) | 1 (8.3%) |
| Jewish | 0 (0%) | 0 (0%) |
| Muslim | 0 (0%) | 1 (8.3%) |
| Sikh | 0 (0%) | 0 (0%) |
| Hindu | 2 (20%) | 0 (0%) |
| Buddhist | 0 (0%) | 0 (0%) |
| Atheist (do not believe in God) | 1 (10%) | 4 (33%) |
| Agnostic (believe that existence of God is unknowable) | 0 (0%) | 3 (25%) |
| Other | 0 (0%) | 0 (0%) |
| Prefer not to say | 0 (0%) | 0 (0%) |
| Attendance of religious services in past 12 months | | |
| Never | 2 (20%) | 9 (75%) |
| Seldom | 0 (0%) | 0 (0%) |
| A few times a year | 4 (40%) | 3 (25%) |
| Once or twice a month | 1 (10%) | 0 (0%) |
| Once a week | 0 (0%) | 0 (0%) |

| Variable | High moral incongruence, N = 10 | Low moral incongruence, N = 12 |
|---|---|---|
| More than once a week | 3 (30%) | 0 (0%) |
| Frequency of masturbation with pornography use in past 4 weeks | | |
| Never | 0 (0%) | 2 (17%) |
| Less than once a week | 1 (10%) | 0 (0%) |
| 1-2 times a week | 3 (30%) | 1 (8.3%) |
| 3-4 times a week | 1 (10%) | 1 (8.3%) |
| 5-6 times a week | 1 (10%) | 4 (33%) |
| 1-2 times a day | 3 (30%) | 3 (25%) |
| More than twice a day | 1 (10%) | 1 (8.3%) |
| Frequency of masturbation without pornography use in past 4 weeks | | |
| Never | 6 (60%) | 4 (33%) |
| Less than once a week | 3 (30%) | 4 (33%) |
| 1-2 times a week | 0 (0%) | 2 (17%) |
| 3-4 times a week | 1 (10%) | 1 (8.3%) |
| 5-6 times a week | 0 (0%) | 0 (0%) |
| 1-2 times a day | 0 (0%) | 1 (8.3%) |
| More than twice a day | 0 (0%) | 0 (0%) |
| Frequency of sexual intercourse in past 4 weeks | | |
| Never | 8 (80%) | 7 (58%) |
| Less than once a week | 1 (10%) | 2 (17%) |
| 1-2 times a week | 1 (10%) | 3 (25%) |
| 3-4 times a week | 0 (0%) | 0 (0%) |
| 5-6 times a week | 0 (0%) | 0 (0%) |
| 1-2 times a day | 0 (0%) | 0 (0%) |
| More than twice a day | 0 (0%) | 0 (0%) |

**Examining Sexual Episodes**

In total, there were 162 instances of participants using pornography (with or without masturbation), compared to 26 instances of participants masturbating without pornography, and 13 instances of participants having intercourse with a partner. Figure 13 contains boxplots showing the length of all recorded sexual episodes. In terms of length of episode, masturbation coupled with pornography use had the greatest variation, with a range from 1 to 500 minutes. The longest episode of masturbation without pornography use was only 30 minutes long, while the longest episode of sexual intercourse was 90 minutes long. In contrast, there were 15 episodes of pornography use over 100 minutes long, and 5 episodes over 200 minutes long, from more than one participant. This may suggest that some pornography users found content that sustained their interest for considerably longer than masturbation or sexual intercourse alone.

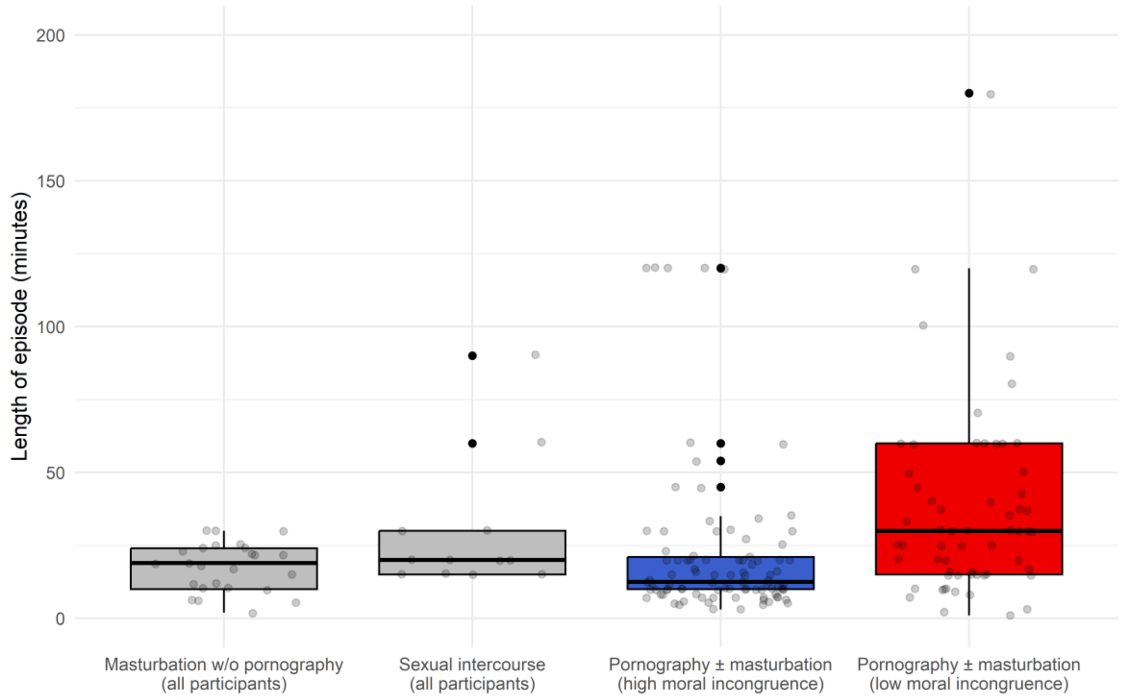


*Figure 13: Boxplots with horizontally jittered data points showing the length of different types of sexual episode. Due to an insufficient sample size, masturbation without pornography and sexual intercourse could not be categorised into low and high moral incongruence groups. Note that the y-axis has been truncated at 200 minutes to show differences between groups more clearly. Above this, there was one outlier for the high moral incongruence group (300 minutes), and four outliers for the low moral incongruence group (240, 480, 480, and 500 minutes).*

Participants with high moral incongruence had a shorter mean length of pornography use of 25.93 minutes compared to 61.01 minutes for low moral incongruence ($p_{t\text{-test}} = 0.011$). This significant difference remained even when outliers above 200 minutes were excluded, with mean episode lengths of 22.99 minutes for high moral incongruence versus 37.15 minutes for low moral incongruence ($p_{t\text{-test}} = 0.0064$). Further, a moderate inverse correlation was found between moral incongruence score and duration of episodes of pornography use with masturbation (r = -0.34, p < 0.001). However, no significant correlation was found between moral incongruence score and duration of masturbation-only episodes (r = -0.21, p = 0.32).

Figure 14 shows mood scores obtained outside of pornography use, and participants' highest perceived mood scores during pornography use (either accompanied by or without masturbation or orgasm). Both mood and highest perceived mood were measured on the same 0-10 scale. Wilcoxon rank sum tests with false discovery rate corrections applied revealed no significant difference between mood scores obtained outside of pornography use when comparing low and high moral incongruence participants (p = 0.44). However, all other comparisons showed significant differences. The most notable difference was observed in the highest mood scores during pornography use between participants with low and high moral incongruence (p = 0.0013).

This indicates that participants with low moral incongruence experienced a greater increase in mood during pornography use than participants with high moral incongruence, suggesting that relative enjoyment of pornography use was higher for low moral incongruence participants.

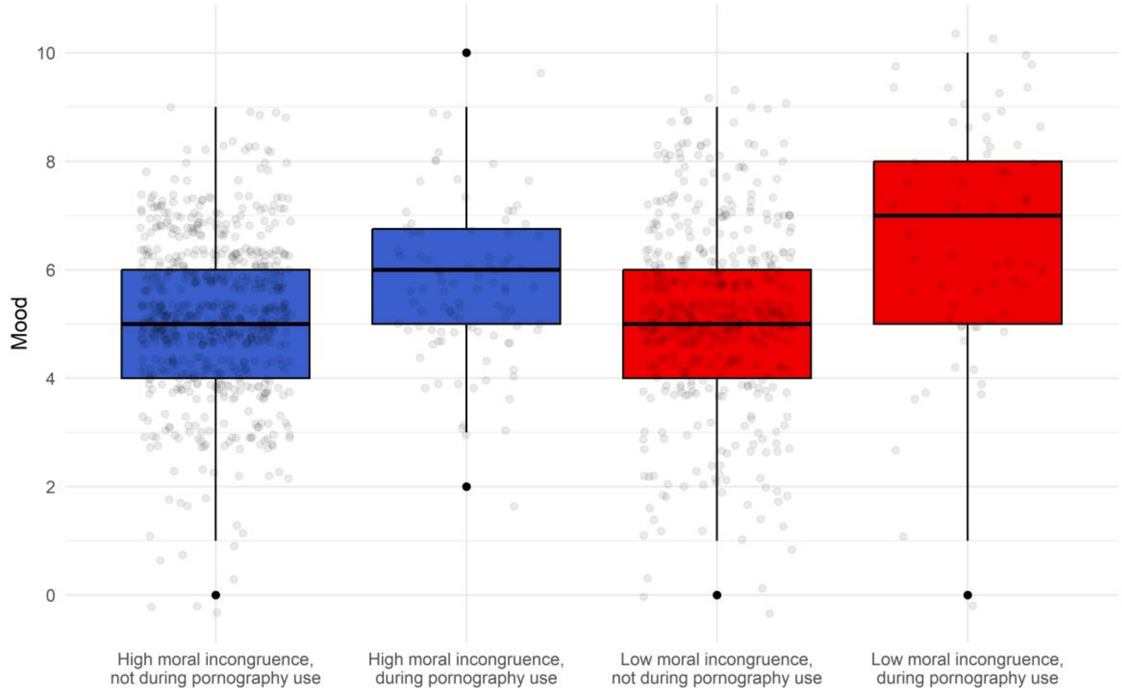


*Figure 14: Boxplots with jittered data points comparing the highest mood scores experienced during pornography use (either with or without masturbation or orgasm), and mood scores experienced outside of pornography use, for low and high moral incongruence participants.*

**Descriptive Statistics for EMA Variables**

Table 2 contains descriptive statistics for the mental health variables included in the EMA, for both high and low moral incongruence participants. Both craving and affect variables exhibited high within-person standard deviations across groups, suggesting dynamic fluctuations in both emotional and motivational states for most participants, consistent with expectations. Craving variables showed low median values in both groups, suggesting a bursty pattern characterized by intermittent spikes in craving. Guilt, shame, loneliness, and relationship connectedness showed the highest intraclass correlation coefficients (all > 0.5 for both groups), suggesting that these variables varied more between individuals than within individuals. In contrast, the remaining variables had intraclass correlation coefficients below 0.5 for both groups, reflecting greater within-person than between-person variability.

*Table 2: Descriptive statistics for mental health variables from EMA. SD = standard deviation, ICC = intraclass correlation.*

| Level of moral incongruence | Variable | Mean | SD | Median | Within-person SD | Between-person SD | ICC |
|---|---|---|---|---|---|---|---|
| High moral incongruence | Mood | 5.17 | 1.43 | 5 | 1.32 | 0.60 | 0.14 |
| | Relationship connectedness | 4.39 | 2.07 | 4 | 1.35 | 1.46 | 0.53 |
| | Craving for pornography | 1.53 | 2.35 | 0 | 2.08 | 1.52 | 0.31 |
| | Craving for sex | 2.06 | 2.58 | 0 | 1.95 | 1.75 | 0.43 |
| | Loneliness | 3.98 | 2.72 | 4 | 1.77 | 1.91 | 0.53 |
| | Guilt | 3.19 | 2.48 | 2 | 1.76 | 1.93 | 0.52 |
| | Shame | 3.20 | 2.58 | 2 | 1.73 | 2.22 | 0.60 |
| | Anxiety | 3.01 | 1.91 | 3 | 1.51 | 1.15 | 0.36 |
| | Difficulty thinking | 2.86 | 2.18 | 3 | 1.83 | 1.11 | 0.25 |
| Low moral incongruence | Mood | 5.22 | 1.74 | 5 | 1.51 | 1.06 | 0.29 |
| | Relationship connectedness | 5.31 | 3.50 | 5 | 1.62 | 2.91 | 0.76 |
| | Craving for pornography | 1.98 | 2.43 | 1 | 2.16 | 1.63 | 0.28 |
| | Craving for sex | 2.49 | 2.62 | 2 | 2.10 | 2.04 | 0.43 |
| | Loneliness | 3.39 | 2.78 | 3 | 1.69 | 2.76 | 0.71 |
| | Guilt | 3.37 | 2.92 | 2 | 1.84 | 2.74 | 0.67 |
| | Shame | 3.33 | 3.05 | 2 | 1.87 | 2.66 | 0.66 |
| | Anxiety | 3.30 | 2.29 | 3 | 1.92 | 1.81 | 0.41 |
| | Difficulty thinking | 3.72 | 2.45 | 3 | 2.30 | 1.36 | 0.16 |

Figure 15 shows the within-person Pearson correlations between different mental health variables measured during the EMA. The strongest correlations were observed between guilt & shame, guilt & loneliness, shame & loneliness, and craving for pornography & craving for sexual intercourse. On the other hand, the strongest negative correlations were identified between relationship connectedness & loneliness, mood & loneliness, and mood & anxiety.

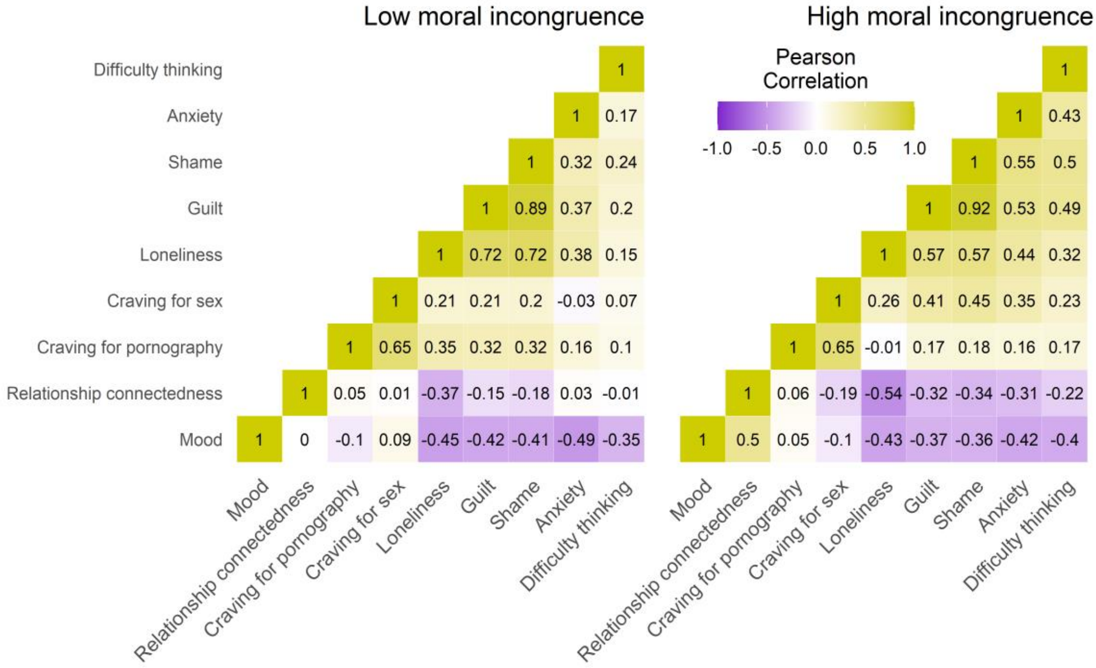


*Figure 15: Within-person Pearson correlations between wellbeing variables during EMA.*

**Temporal Dynamics of Mental Health Variables**

A table of model coefficients for the Bayesian model fitting process, and plots of selected models are presented in Appendices B and C. The sample size was insufficient to produce a meaningful comparison across different types of sexual episodes. Specifically, there was not enough data to differentiate between pornography use combined with masturbation and masturbation alone (Prause, 2017), as only 26 (15%) of the 178 masturbation episodes were not accompanied by pornography use. There were also only 13 episodes of sexual intercourse recorded. Consequently, during the model fitting process, I merged instances of masturbation alone with those involving pornography use, and ignored episodes of sexual intercourse. This allowed me to analyse two groups of sexual episodes:

- Group A: Episodes involving pornography use, whether or not accompanied by masturbation or orgasm.
- Group B: All Group A episodes, plus episodes of masturbation without pornography use.

For high moral incongruence participants, there was very strong evidence that guilt increased following both Group A and Group B episodes, before decaying to baseline ($BF_{10} > 1000$ for all models). For low moral incongruence participants, there was moderate to strong evidence that guilt increased following both Group A (non-truncated data only, $BF_{10} = 6.16$) and Group B (non-truncated data only, $BF_{10} = 77.99$) episodes. There was strong to very strong evidence that post-episode guilt spikes, which decayed exponentially, were larger in the high moral incongruence group than in the low moral incongruence group across all models ($BF_{10}$ ranged from 27.32 for non-truncated Group A data to 577.6 for non-truncated Group B data). There was also strong evidence that guilt increased prior to Group B episodes for high moral incongruence participants (truncated data only, $BF_{10}$ = 11.82); for this model, there was weak evidence for a difference between the magnitude of pre-episode guilt spikes for high versus low moral incongruence participants ($BF_{10}$ = 4.004). All models for guilt are shown in Figure 16.

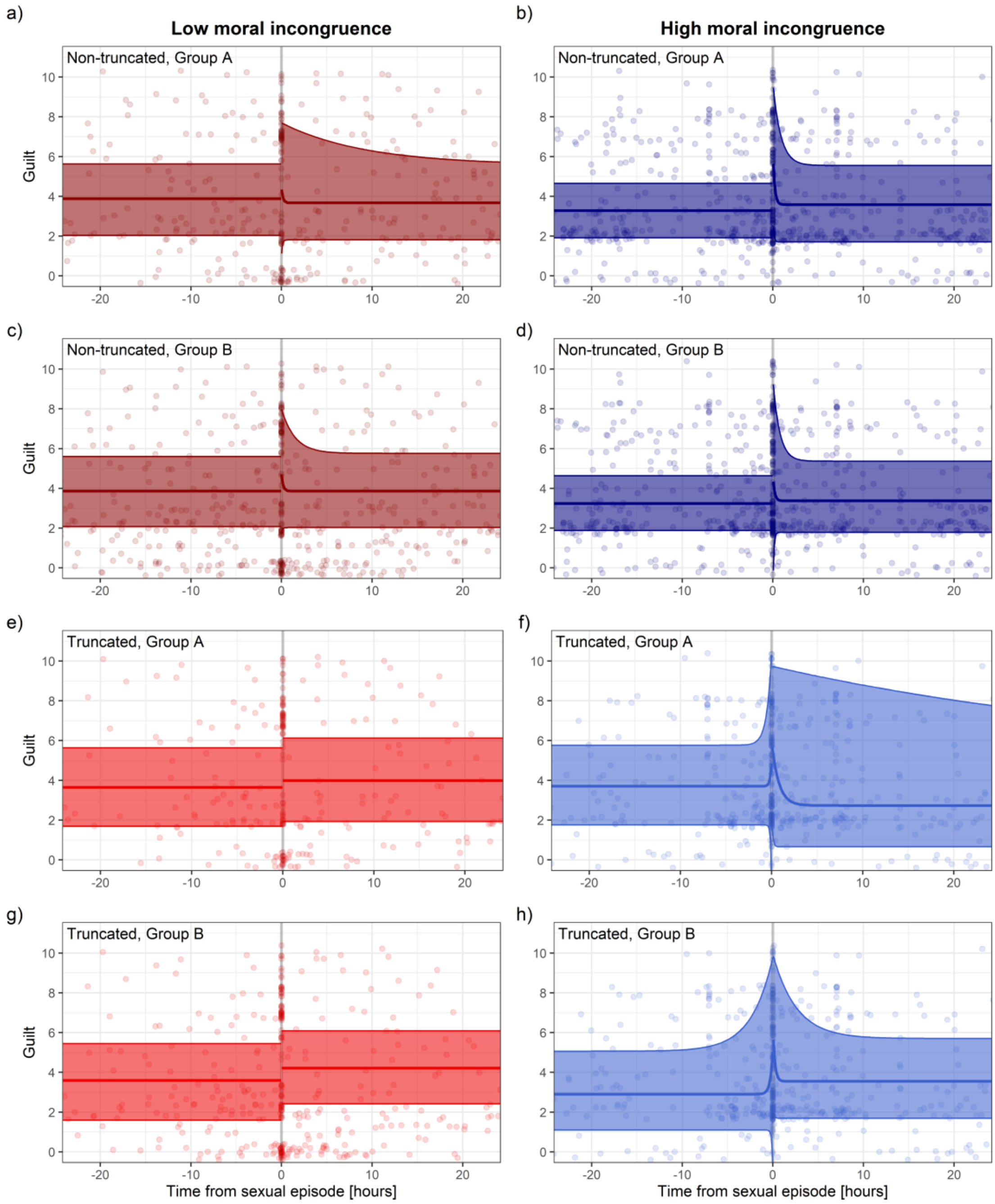


*Figure 16: Results from fitting hierarchical exponential models to guilt scores obtained pre- and post-sexual episodes, showing 24 hours before and after episodes. Graphs on the left are for low moral*

*incongruence participants, while graphs on the right are for high moral incongruence participants. Error ribbons represent 95% credible intervals. Exponential models are presented in cases where $BF_{10}$ > 1, indicating evidence in favour of the alternative hypothesis (exponential model), while horizontal models indicate cases where $BF_{01}$ > 1, indicating evidence in favour of the null hypothesis (no effect). Note that due to the high correlation between guilt and shame, the shame results are very similar to these results. Group A: any episodes of pornography use, either with or without masturbation or orgasm. Group B: any episodes of pornography use, either with or without masturbation or orgasm, plus episodes of masturbation without pornography use.*

For aggregated within-participant EMA data, shame was strongly correlated with guilt ($r_{\text{low moral incongruence}}$ = 0.89, $r_{\text{high moral incongruence}}$ = 0.92), meaning that directionally, the models for shame and guilt were similar. For high moral incongruence participants, there was moderate to very strong evidence that shame increased prior to Group A episodes (truncated data, $BF_{10}$ = 7.56; non-truncated data, $BF_{10}$ = 233.16), and strong to very strong evidence that shame increased prior to Group B episodes (truncated data, $BF_{10}$ = 19.88; non-truncated data, $BF_{10}$ > 1000). There was also very strong evidence that shame increased following both Group A and Group B episodes before decaying to baseline ($BF_{10}$ > 1000 for all models except for truncated Group B data). For low moral incongruence participants, there was weak to moderate evidence that shame increased following Group B episodes before decaying to baseline (truncated data, $BF_{10}$ = 3.86; non-truncated data, $BF_{10}$ = 9.35). There was weak to strong evidence for a difference in the magnitude of post-episode shame spikes between low and high moral incongruence participants for post-episode Group B models (truncated data, $BF_{10}$ = 4.738; non-truncated data, $BF_{10}$ = 21.04). For Group A models, there was weak to moderate evidence for no difference in magnitude of pre-episode shame spikes between low and high moral incongruence participants (truncated data, $BF_{01}$ = 5.605; non-truncated data, $BF_{01}$ = 4.924).

For high moral incongruence participants, I found strong evidence that loneliness increased following Group A episodes, before decaying to baseline (truncated data, $BF_{10}$ = 19.91), and strong to very strong evidence that loneliness increased following Group B episodes, before decaying to baseline (truncated data, $BF_{10}$ = 14.43; non-truncated data, $BF_{10}$ = 714.62). All models for low incongruence participants showed moderate to very strong evidence in favour of the null hypothesis of no effect. There was weak to moderate evidence for the null hypothesis of no difference in the magnitude of post-episode loneliness spikes between low and high moral incongruence participants for the truncated models (Group A, $BF_{01}$ = 3.329; Group B, $BF_{01}$ = 8.137), and inconclusive evidence for the Group B non-truncated model ($BF_{10}$ = 1.004).

Figure 17 contains piecewise functions derived from the parameters of the exponential models for truncated Group A episodes, demonstrating my proposed model of the temporal dynamics of mood in relation to pornography use with masturbation. For high moral incongruence participants, I found strong to very strong evidence that mood decreased following Group A episodes, before decaying to baseline (truncated data, $BF_{10}$ = 66.57; non-truncated data, $BF_{10}$ > 1000), and moderate evidence that mood decreased following Group B episodes, before decaying to baseline (truncated data, $BF_{10}$ = 7.09). I also found strong evidence that for high moral incongruence participants, mood decreased prior to both Group A (truncated data, $BF_{10}$ = 45.03) and Group B episodes (truncated data, $BF_{10}$ = 29.03). All models for low incongruence participants showed inconclusive to strong evidence in favour of the null hypothesis of no effect. I found very strong evidence for a difference in the magnitude of post-episode mood dips between low and high moral incongruence participants for truncated post-episode mood models (Group A, $BF_{10}$ = 1881; Group B, $BF_{10}$ = 254.1). However, there was also moderate evidence for no difference in post-episode mood dip magnitudes for non-truncated Group B data ($BF_{01}$ = 6.757), and weak evidence for no difference in pre-episode mood changes between low and high moral incongruence participants for Group B truncated data ($BF_{01}$ = 4.7619).


*Figure 17: Simplified model of temporal dynamics of mood in relation to pornography use with masturbation, moderated by moral incongruence, showing an opponent process pattern for high moral incongruence participants. Piecewise functions were derived from Bayesian models for truncated Group A episodes, with mood at $t = 0$ calculated as the mean 'highest mood' score recorded during sexual episodes. Note that the length of each episode has not been taken into account. Also, the evidence for a difference in pre-episode mood dip magnitude between low and high moral incongruence participants was inconclusive for Group A episodes.*

Craving for sexual intercourse was strongly correlated with craving for pornography (within-person r = 0.65 for both low and high moral incongruence). For low moral incongruence participants, I found strong evidence that craving for pornography increased following Group A episodes, before decaying to baseline (truncated data, $BF_{10}$ = 29.96), and very strong evidence that craving for pornography increased following Group B episodes, before decaying to baseline (truncated data, $BF_{10}$ = 144.92). For high moral incongruence participants, I found weak evidence that craving for sexual intercourse increased following Group A episodes (truncated data, $BF_{10}$ = 3.81). Further, I found strong to very strong evidence for a significant difference in the magnitude of pre- and post-episode craving spikes for the truncated Group A models (post-episode, $BF_{10}$ = 65.36; pre-episode, $BF_{10}$ > 1000). There was also weak to very strong evidence in favour of the null hypothesis of no effect prior to sexual episodes for both levels of moral incongruence, and for both types of craving. However, a visual inspection of the data revealed distinct spikes in pornography craving approximately 15 to 20 hours before pornography use for high moral incongruence participants (Figure 18), with similar spikes observed for low moral incongruence participants also. These effects were not strong enough to shift the evidence in favour of the exponential models.

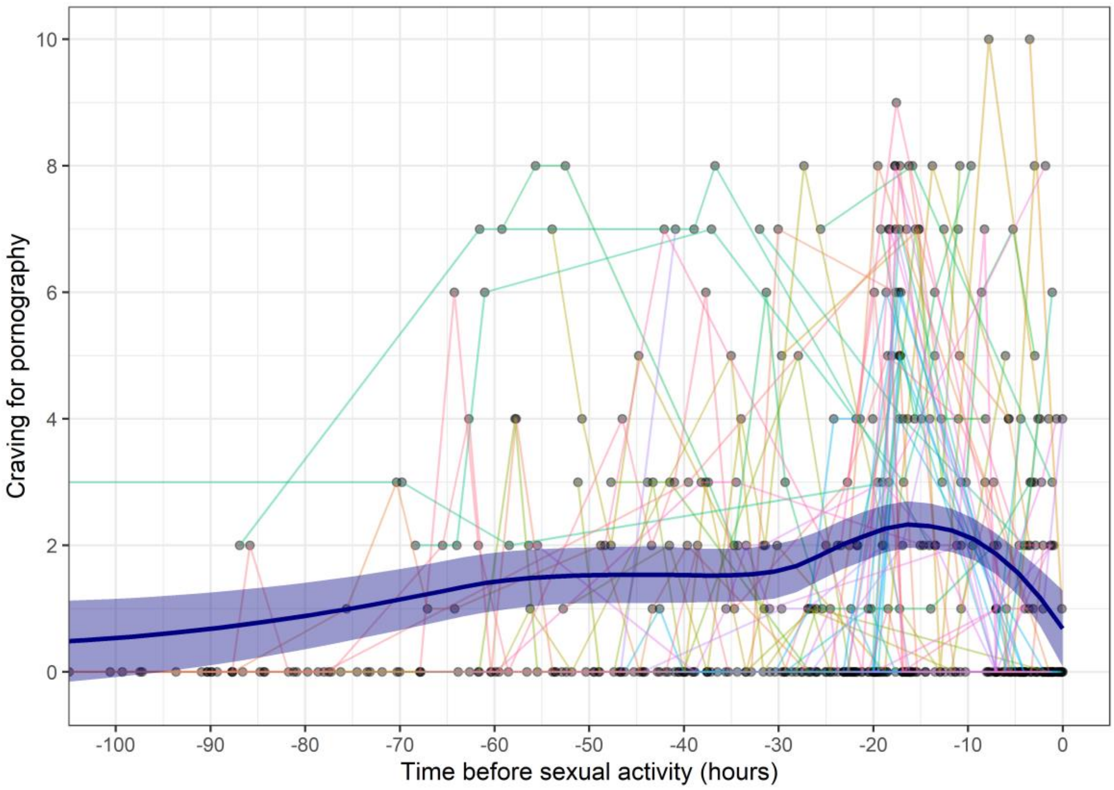


*Figure 18: Example of temporary spike in craving for pornography around 15 to 20 hours prior to pornography use, with LOESS (locally estimated scatterplot smoothing) line fitted, for high moral incongruence participants only. This phenomenon was consistently observed across all models for high moral incongruence participants and in multiple participants. Different coloured lines represent different periods of abstinence between sexual episodes.*

For high moral incongruence participants, there was very strong evidence that difficulty thinking increased following Group A episodes, before decaying to baseline (non-truncated data,

$BF_{10}$ = 618.7), and strong to very strong evidence that difficulty thinking increased following Group B episodes, before decaying to baseline (truncated data, $BF_{10}$ = 23.52; non-truncated data, $BF_{10}$ > 1000). For low moral incongruence participants, there was very strong evidence that difficulty thinking increased following Group B episodes, before decaying to baseline (non-truncated data, $BF_{10}$ > 1000), while there was very strong evidence that difficulty thinking increased prior to Group B episodes ($BF_{10}$ > 1000 for non- and truncated data), and moderate evidence that difficulty thinking increased prior to Group A episodes (non-truncated data, $BF_{10}$ = 8.49). I found moderate evidence for a difference in the magnitude of post-episode spikes in difficulty thinking between low and high moral incongruence participants for the post-episode truncated Group B model ($BF_{10}$ = 6.108), but also found weak to moderate evidence for no difference in post-episode spike magnitude for non-truncated data (Group A, $BF_{01}$ = 4.297; Group B, $BF_{01}$ = 5.886). All models for difficulty thinking are shown in Figure 19.

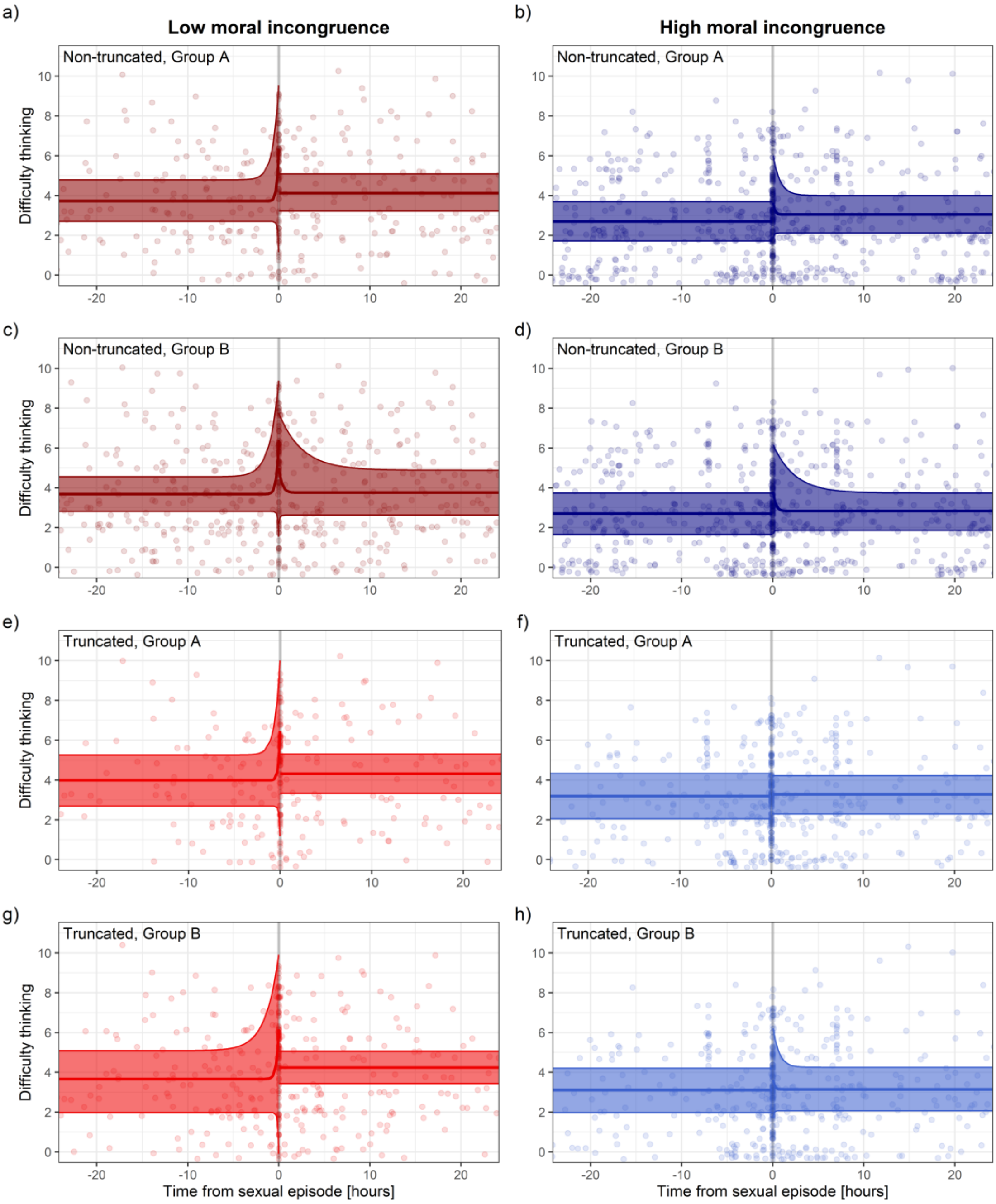


*Figure 19: Results from fitting hierarchical exponential models to 'difficulty thinking' scores obtained pre- and post-sexual episodes, showing 24 hours before and after episodes. Graphs on the left are for low moral incongruence participants, while graphs on the right are for high moral incongruence participants. Error ribbons represent 95% credible intervals. Exponential models are presented in cases where $BF_{10} > 1$, indicating evidence in favour of the alternative hypothesis (exponential model), while horizontal models indicate cases where $BF_{01} > 1$, indicating evidence in favour of the null hypothesis (no effect). Group A: any episodes of pornography use, either with or without masturbation or orgasm. Group B: any episodes of pornography use, either with or without masturbation or orgasm, plus episodes of masturbation without pornography use.*

For high moral incongruence participants, I found very strong evidence that relationship connectedness decreased following Group A episodes, before decaying to baseline ($BF_{10} > 1000$ for non- and truncated data), and very strong evidence that relationship connectedness decreased following Group B episodes, before decaying to baseline (non-truncated data, $BF_{10} > 1000$). I also found very strong evidence that for high moral incongruence participants, relationship connectedness decreased prior to Group A episodes (non-truncated data, $BF_{10} = 78.38$) and decreased prior to Group B episodes (non-truncated data, $BF_{10} = 81.84$). All models for low incongruence participants showed inconclusive to very strong evidence in favour of the null hypothesis of no effect. I found strong evidence for a difference in the magnitude of post-episode dips in relationship connectedness between low and high moral incongruence participants for the post-episode truncated Group B model for relationship connectedness ($BF_{10} = 23.73$). However, I also found weak to moderate evidence for no difference in post-episode dips in relationship connectedness between low and high moral incongruence participants for the non-truncated data (Group A, $BF_{01} = 5.848$; Group B, $BF_{01} = 3.943$).

For low moral incongruence participants, I found weak evidence that anxiety decreased prior to Group B episodes (truncated data, $BF_{10} = 4.29$). All other models for both low and high moral incongruence participants showed inconclusive to very strong evidence in favour of the null hypothesis of no effect. I found very strong evidence for a difference in pre-episode spike magnitude in anxiety between low and high moral incongruence participants for the truncated Group B models ($BF_{10} = 2.498e+06$). I also found weak evidence in favour of no difference in pre-episode anxiety changes between low and high moral incongruence participants for the non-truncated Group A models ($BF_{01} = 4.572$).

### Content Analysis of Pornography Use Triggers

Participant's responses to the open-ended question about triggers leading up to pornography use or masturbation were categorised according to Table 3. I performed a content analysis of these responses, identifying feature categories during the review process. Given that there was insufficient data to conduct a comparison between these groups, data was combined for all sexual episodes and for both high and low moral incongruence.

*Table 3: Coding scheme used to categorise open-ended responses about triggers leading up to sexual episodes.*

| **Feature category** | **Type of feature** |
|---|---|
| Sleep | Sleep aid, pre-sleep routine, waking routine, couldn't sleep, or disturbed sleep |
| Craving | Craving for pornography, arousal, or 'horniness' |

| | |
|---|---|
| Bored | Boredom, nothing to do |
| Stressed | Stress, overwhelm, burnout |
| Internet/Social Media | Browsing the Internet or social media |
| Loneliness/Alone | Feelings of loneliness, or being alone/isolated |
| Tired | Feelings of tiredness |
| Thoughts | Sexual thoughts or fantasies |
| Work | Work, school, or studying |
| Habit | Habit or routine |
| Bedroom | In bedroom or in bed |
| Drugs | Alcohol or marijuana |
| Distraction | Needed a distraction or procrastinating |
| Interaction | Real-life interaction with attractive person |
| Anxiety | Feelings of anxiety |
| Date | Went on a date with no sexual intercourse |
| Unattractive | Felt unattractive or wanted to feel more attractive |
| Dream | Sexual dream |
| Other | Other or unknown triggers |

The six most mentioned triggers (Figure 20) were Sleep (49), Craving (31), Internet/Social Media (26), Bored (26), Loneliness/Alone (25), and Stressed (21). Despite Craving, Loneliness, and (to a lesser extent) Anxiety being frequently cited as triggers, these variables did not show significant increases prior to sexual episodes in any of the quantitative models. Possible reasons for this are discussed below.

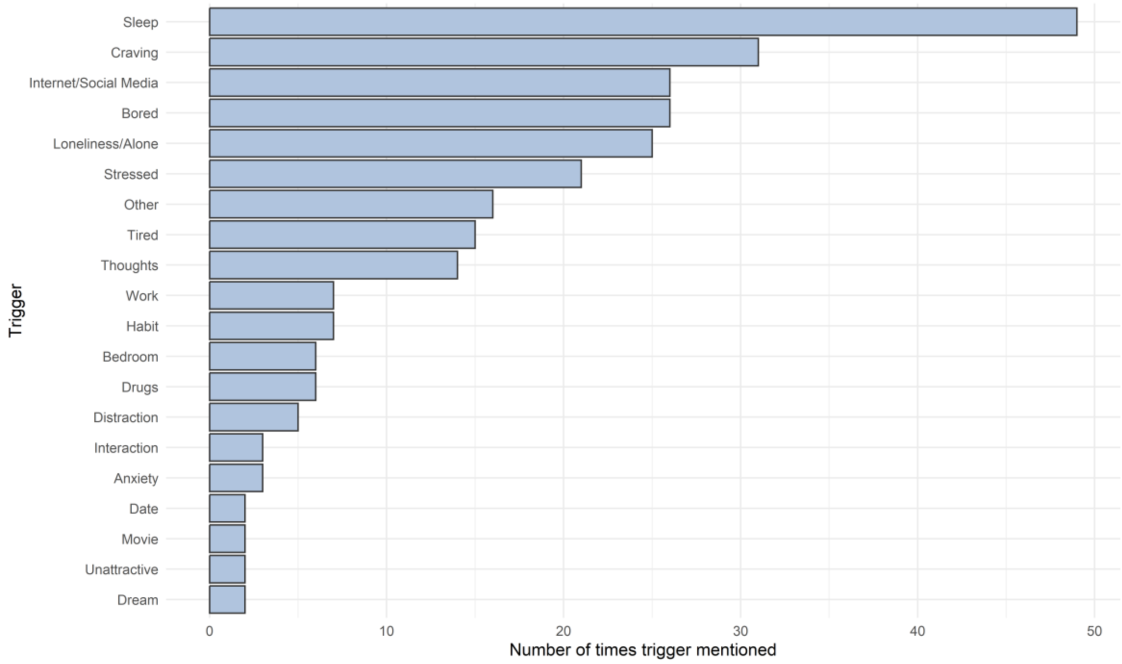


*Figure 20: Tally of triggers leading up to pornography use or masturbation. Only triggers with at least two recorded instances were plotted.*

***Discussion***

To my knowledge, this is the first study to quantify the temporal dynamics associated with pornography use and masturbation. Overall, high moral incongruence participants were more likely to experience negative emotional and cognitive effects related to pornography use and masturbation compared to low moral incongruence participants. Prior to pornography use and masturbation, high moral incongruence participants experienced increased guilt and shame, along with decreased mood and relationship connectedness. By contrast, low moral incongruence participants experienced reduced anxiety and increased difficulty thinking. Following pornography use with masturbation, high moral incongruence participants experienced temporarily increased guilt, shame, loneliness, difficulty thinking, and craving for sexual intercourse, as well as worsened mood and relationship connectedness. On the other hand, following pornography use with masturbation, low moral incongruence participants only experienced temporarily increased guilt and shame (but to a lesser degree than high moral incongruence participants), difficulty thinking, and craving for pornography. Hence, the evidence provided here suggests that pornography use with masturbation may exacerbate symptoms of guilt, shame, loneliness, depression, and relationship disconnectedness (at least temporarily) rather than relieve them.

### Implications of Temporal Dynamics Analysis

These findings provide preliminary evidence that moral incongruence moderates the relationship between pornography use, masturbation, and the temporal dynamics of mental wellbeing. In particular, this moderation is evidenced by the heightened feelings of guilt and shame experienced by high moral incongruence participants both before and after sexual episodes, in contrast to those with low moral incongruence.

Recently, Henry et al. (2023) proposed a computational model of opponent processes demonstrating how a frequently repeated addictive behaviour may generate hedonic allostasis, leading to depression. These findings regarding mood suggest a pattern consistent with opponent process theory. Specifically, high moral incongruence participants experienced a decrease in mood prior to pornography use, which may or may not have led to them using pornography. During the sexual episode, these participants experienced a peak mood that exceeded baseline (the 'a-process'), then experienced a reversal in mood that dropped below baseline and decayed over time (the 'b-process') (Solomon & Corbit, 1974). Yet mood also decreased prior to pornography use for high moral incongruence participants, creating a triphasic opponent process pattern. Therefore, I believe this is the first paper to demonstrate a possible causal mechanism for a bidirectional relationship between PPU and depression for high moral incongruence subjects.

These findings may also help explain Perry's results (2018), which showed that men who morally reject pornography are more likely to experience depression even with low use, while for those who don't morally reject pornography, depression is only associated with high-frequency use. This also aligns with Henry et al.'s (2023) opponent process theory of PPU, which suggests that individuals with low moral incongruence only experience a small b-process after pornography use, although this can lead to hedonic depression due to allostasis at high pornography use frequencies. In contrast, those with high moral incongruence experience a larger b-process, leading to depression even at low pornography use frequencies. The b-process in low moral incongruence participants might be too small to detect in this study, partly due to sample size limitations. More data is needed to validate this theory.

If pre-episode decreases in mood are associated with spikes in craving, then this fits the pattern of an addictive cycle consisting of three phases: binge/intoxication, withdrawal/negative affect, and preoccupation/anticipation (Koob & Volkow, 2016; Volkow et al., 2011). Thus, I believe this is also the first paper to empirically demonstrate a possible causal mechanism for how pornography use may follow a pattern of addiction for subjects with high moral incongruence. Future research should test whether similar triphasic opponent process patterns are present in other wellbeing variables, as mood was the only variable measured within sexual episodes in this study. The hypothesis that moral incongruence is necessary to produce these patterns should also be tested explicitly.

There is possible evidence for post-episode ‘brain fog’ based on the observed spikes in ‘difficulty thinking’ following pornography use. Both low and high moral incongruence participants experienced spikes in difficulty thinking following pornography use with masturbation. However, low moral incongruence participants also experienced increased difficulty thinking before sexual episodes, unlike their high moral incongruence counterparts. For within-person data from high moral incongruence participants, difficulty thinking was moderately correlated with shame ($r = 0.50$), guilt ($r = 0.49$), decreased mood ($r = 0.40$), and loneliness ($r = 0.32$), suggesting the post-episode emotional overwhelm of these symptoms may produce cognitive difficulties akin to brain fog. These preliminary findings, though requiring further investigation, could potentially account for some of the unexplained symptoms (such as brain fog) reported by those in online forums such as r/NoFap, a forum dedicated to helping people quit pornography use (Chasioti & Binnie, 2021).

The lack of evidence for a temporal relationship between anxiety and pornography use was surprising, given that several studies have shown a correlation between PPU and increased anxiety (Vieira & Griffiths, 2024). I was also surprised to observe that loneliness did not increase prior to pornography use episodes, as there were 25 instances of ‘Loneliness/Alone’ being mentioned as a trigger in the content analysis. The literature suggests a possible bidirectional relationship between loneliness and PPU, where individuals use pornography to cope with loneliness, which may exacerbate feelings of loneliness, especially for those who have difficulty forming relationships (Mestre-Bach & Potenza, 2023a; Vescan et al., 2024). One possible explanation is that participants’ post-hoc analysis of the events leading to pornography use differed from the sensations felt prior to the episode. It may be that craving produces a masking effect that makes it difficult to interpret one’s true emotional state in the moment. Alternatively, an exponential model may not be optimal for explaining the temporal dynamics of these variables prior to sexual activity.

The decrease in relationship connectedness before and after sexual episodes for high moral incongruence participants suggests a possible bidirectional link between pornography use and reduced feelings of connectedness to others. This supports prior studies that indicate that higher pornography use negatively impacts perceived relationship quality, although this effect is moderated by the partner's moral and religious beliefs (Ruffing et al., 2022; Szymanski et al., 2015), and by the partner's awareness of pornography use (Vaillancourt-Morel et al., 2024).

The evidence for an increase in craving for pornography or sexual intercourse prior to sexual episodes was inconclusive, which was surprising given that craving was mentioned as a trigger 31 times in the open-ended responses. This was a surprising finding, given that craving incubation prior to addictive behaviours such as pornography use is well documented (Allen et al., 2017; Fernandez et al., 2021b; Kober et al., 2010; Potenza, 2008; Starcke et al., 2018; Venniro et al., 2021; Volkow et al., 2011). Furthermore, for some models, I detected increases in craving for pornography *after* sexual episodes for low moral incongruence participants, and increases in craving for sexual intercourse *after* sexual episodes for high moral incongruence participants, which was also unexpected, and may be indicative of sensitisation effects. While these results show some evidence suggestive of intermittent spikes in craving prior to sexual episodes, further research is required to validate these effects. However, if validated, this may indicate an opportunity for intervention using established techniques such as cognitive behavioural therapy, mindfulness, and 'urge surfing' for managing intermittent cravings by redirecting attention (Briken, 2020; Parsons et al., 2007).

### Length and Enjoyment of Sexual Episodes

The difference in length and enjoyment of pornography use episodes between low and high moral incongruence may suggest different motivations for use. One hypothesis could be that participants with high moral incongruence were more likely to use pornography quickly to alleviate unpleasant feelings (such as low mood), while participants with low moral incongruence might use pornography to alleviate boredom or for extended bouts of pleasure. Maitland and Neilson (2023) showed that individuals who use pornography mainly for enjoyment have social wellbeing levels similar to those who do not use pornography, while individuals with varied motivations for pornography use and associated negative outcomes often struggle with social wellbeing, which affects their intimate relationships. Hence, motivation for use may play a role in determining whether pornography use is problematic.

However, these results also possibly show a benefit to moral incongruence in terms of unproductive time saved, since there was a pronounced difference in mean length of pornography use episodes when comparing low to high moral incongruence individuals (61.01 vs 25.93 minutes). These results may also support the 'supernormal stimulus' hypothesis, which suggests that pornography hijacks the human's sexual drive with its endless novelty capable of maintaining sexual arousal for unusually long periods (Barrett, 2010; Hilton Jr, 2013; Koukounas & Over, 2000). Alternatively, participants with high moral incongruence may have under-reported the duration of their sexual episodes due to increased feelings of guilt and shame.

### Implications of Qualitative Analysis

In order to not overburden participants, I prioritised certain variables in the EMA analysis and excluded others. However, the content analysis identified several of these excluded variables, such as stress, tiredness, boredom, intrusive sexual thoughts, Internet and social media use, and timing factors (e.g., before sleep, just after waking up, or after work). Future studies could ask about these factors either before or during the EMA. In particular, seasonal variables such as participants' Internet use, work and sleep schedules should be examined.

Future research should consider adding both proximal and distal qualitative markers (Witkiewitz & Marlatt, 2007), such as post-episode questions about how participants feel immediately after pornography use. This could help clarify the sensations experienced and explain possible links between well-studied variables, such as guilt and shame, and less well-examined variables, such as brain fog. Additionally, studying the content of the pornography used is important, as different types have been linked to varying levels of sexual satisfaction (Nolin et al., 2024) and may produce differing a- and b-process magnitudes. However, since EMA is more intensive than other survey methods, researchers must be careful not to burden participants with too many questions. For this reason, and due to predicted statistical limitations and low sample size, I selected EMA variables that were less likely to show seasonal patterns. Future research should consider including these variables and controlling for seasonal effects. For example, although I excluded 'boredom' due to its likely association with work hours, the qualitative analysis showed its importance as a trigger for specific participants. Masturbation as a stress-relief mechanism is also well-documented across genders (Csako et al., 2022; Hevesi et al., 2023; Wehrli et al., 2024). Moreover, these findings highlighted the role of sleep and work schedules in triggering cravings, with pornography use often occurring as a sleep aid or after waking up, and for stress relief post-work.

Several participants reported that unintentionally viewing sexual content on the Internet or social media was a trigger for them, with YouTube, Reddit, Instagram, and Twitter being specific platforms mentioned. In the study by Fernandez et al., electronic media (e.g., "Dating sites, Instagram, Facebook, movies/TV, YouTube, online ads") were the most common source of external triggers leading to relapse for members of Reboot Nation (Fernandez et al., 2021b). This suggests a growing problem for those struggling with PPU, as even casual Internet browsing may pose a high risk of triggering pornography use. In this study, 27% of the EMA participants reported using an app or software to block sexual content on their devices. This aligns with a content analysis by Henry et al. (2022), which found that content-blocking apps were the most commonly downloaded to reduce PPU. More research is needed to study the effectiveness of these apps.

### Limitations

The primary limitation of this study was the small sample size (n=22), increasing the uncertainty of parameter estimates in the hierarchical models and reducing our ability to draw broad conclusions that can generalize to the broader population. While the repeated measures in EMA data may yield sufficient power for within-person analyses, they are typically insufficient for reliable between-person modelling if sample sizes are small. Future EMA research should use the parameters derived from our results to conduct power calculations and determine appropriate sample sizes required for more robust inferences. Financial incentives should also be included to improve participant retention and compliance, as well as to increase sample size, thereby improving the potential to draw more generalizable conclusions from the data. Additionally, a stratified sampling approach should be applied to ensure sufficient representation of under-reported subgroups, such as female gender and individuals with low moral incongruence, given the likely overrepresentation of men with high moral incongruence in many online forums targeting PPU treatment.

There was also not enough data to analyse the effects of masturbation on its own versus masturbation and pornography use combined (Prause, 2017). There were only 26 instances of masturbation without pornography use, making it impossible to compare this against pornography use with masturbation (152 instances), or even against pornography use by itself (10 instances) or sexual intercourse (13 instances). Future research should account for these low rates and factor them into recruitment. Additionally, efforts to incorporate participant-level random effects led to overfitting and convergence challenges in certain exponential models, likely stemming from insufficient data. In these cases, the Bayes Factor leaned heavily in favour of the null hypothesis of no effect. To address these issues, future EMA studies should aim for larger sample sizes and include participants as random effects to enhance model convergence and parameter estimation.

Irrespective of sample size, we must always be cautious about claiming direct causal effects due to the observational nature of this research. While we can observe that pornography use in some participants precedes negative emotional states, there may be mediating factors involved. For instance, in high moral incongruence participants, pornography use might initially increase guilt and shame, which may then lead to increased loneliness, difficulty thinking, and craving for sexual intercourse, along with worsened mood and relationship connectedness. Furthermore, the differences in temporal dynamics between high and low moral incongruence groups could be influenced by confounding factors. For example, 100% of the high moral incongruence group identified as heterosexual, whereas the low moral incongruence group was more diverse, with 58.3% of this group identifying as bisexual, homosexual, or unsure of their sexual orientation. This variation might be related to religious beliefs, as high moral incongruence participants were generally more religious. Thus, the observed differences could be due to sexual orientation or other factors, rather than solely moral incongruence (Fisher et al., 2019).

Participants were subject to self-selection and self-report biases, having mainly come from the r/pornfree subreddit, which is generally anti-pornography but is less critical of masturbation (*r/pornfree*, 2022). Although I aimed to include participants with a diverse range of moral incongruence scores, the relationship between moral incongruence and study participation is unclear. For example, potential participants with faith practices might find questions about sexual intercourse inappropriate or objectifying, which could affect their willingness to share experiences, especially if they feel shame. The Hawthorne effect—where individuals alter their behaviour because they know they are being observed—may also have influenced participant engagement and responses (Schofield et al., 2019). For instance, participants with high moral incongruence may have been less likely to report a particularly shameful sexual episode in the EMA, or to under-report the length of sexual episodes.

High participant attrition rates and low compliance rates were observed during the EMA, which is consistent with similar previous studies (Bőthe et al., 2021). It is hard to say how financial incentives affected participation; in fact, the exploratory study with no financial incentive had a higher rate of compliance (29%) compared to the pilot study which had a financial incentive (25%), although these rates include participants who did not complete any EMA surveys. Also, participants were drawn from different populations for these two studies, making them difficult to compare. In general, incentives have been used previously to enhance EMA compliance (Goldschmidt et al., 2014) but are not always collected by participants (Burke et al., 2017). Financial incentives are the most widely used and are significantly associated with higher compliance rates when compared to studies with no incentive (Wrzus & Neubauer, 2022). One meta-analysis found that studies of different durations often had no significant difference in compliance rate, likely because longer studies had a lower sampling frequency to reduce participant burden (Wrzus & Neubauer, 2022). Ludwigs et al. (2020) found that compensation for a demanding EMA study increased both compliance rates and reduced sample selectivity. These findings imply that financial incentives, study length, and sampling frequency do influence participant compliance. However, providing financial assistance creates a selection bias towards participants with financial motives. Additionally, a study by Harari et al. (Harari et al., 2017) found that students were less likely to be interested in self-tracking if they were male, older, and lower in agreeableness. Hence, the lack of financial incentives may have a complex influence on attrition during this study, and this should be investigated further in future research.

### *Conclusion*

In conclusion, the 'affective chronometry' approach – using an EMA to measure one's temporal dynamics in response to sexual activity – has provided several unique insights into the relationships between pornography use, masturbation, and mental health. The study findings highlight the complex moderating role of moral incongruence in these relationships and provide a possible mechanism, based on opponent process theory, for how PPU may be addictive and lead to depressed mood, particularly in people with high moral incongruence towards pornography use. Many potential research directions follow from this study, such as exploring opponent process dynamics in mood and other variables, detecting intermittent craving spikes before pornography use, and examining the phenomenon of brain fog after pornography use.

# Chapter 7: Integrative Discussion

The focus of this Chapter is to integrate the findings from each study within the context of current literature, to highlight their limitations, and to suggest new research directions following from this work. To reiterate, the main objectives of this doctorate were:

1) To assess the current state of mobile app therapies for treating problematic pornography use (PPU), highlighting needs for future research on therapeutic options.
2) To evaluate whether opponent process theory is a suitable framework for quantifying the temporal dynamics of pornography use.
3) To determine the direction of causality between pornography use and other mental health variables.
4) To evaluate whether an opponent process model of pornography use can be used to identify safe dose limits for pornography use.

These objectives represent steps toward the ultimate goal of creating improved therapies for PPU sufferers, which is an aim for future researchers and app developers. However, the research conducted during this doctorate has significantly advanced our knowledge of PPU and associated treatment options in the following ways.

In Chapter 3:

1) I characterised the features of mobile apps commonly used to reduce PPU, highlighting the lack of scientific validation for currently available apps. One key finding was that pornography-blocking apps are the most frequently downloaded but tend to have among the lowest user ratings, indicating a high demand for protection from excessive Internet pornography exposure that is not being adequately met with current technologies.
2) I proposed a defence in depth strategy for overcoming PPU, combining complementary features from different mobile applications to reduce PPU.

In Chapter 5:

1) I introduced and formalised behavioural posology, a novel modelling paradigm for quantifying the temporal dynamics of repeatable behaviours. This represents a unique application of a methodology that has been ported across from dynamic systems theory and applied in a behavioural psychology context. Behavioural posology introduces the 'behavioural dose' concept to quantify the $Potency$, $Amount$, $Frequency$, and $Duration$ of repeatable behaviours, enabling them to be modelled similarly to drug doses with pharmacokinetic and pharmacodynamic effects.

2) Using this framework, I replicated Solomon and Corbit's 'standard pattern of affective dynamics' with the PK/PD-based opponent process model, suggesting that behaviours exhibiting this pattern may have underlying components that can be modelled as a compartmentalised neurohormonal system with allostatic properties.

In Chapter 6:

1) I proposed the opponent process model of pornography use, which, when examined with EMA, provided insights into the mechanisms behind the relationships between the temporal dynamics of specific mental health variables that either precede or follow pornography use, thus providing an indication of directionality for these variables.
2) I found that pornography use combined with masturbation appears to impact the temporal dynamics of various mental health variables. These dynamics can be modelled using exponential decay (post-use) and exponential growth (pre-use) models, indicating the potency and timescale of these effects and suggesting the presence of opponent process mechanisms in pornography use.
3) To my knowledge, this paper is the first to provide empirical evidence supporting the hypothesis that opponent process theory provides a mechanism by which pornography use can lead to depressed mood in individuals who experience high moral incongruence regarding its use.

Chapter 3 primarily addressed objective 1, while Chapters 5 and 6 focused on objectives 2-4, with Chapter 5 laying the theoretical and methodological foundation for the analyses in Chapter 6. Objective 3 was only partially met, as the observational design of the IPU study limited causal inference, though it offered preliminary indications of the potential directionality between pornography use and mental health outcomes. Finally, due to our limited sample size in the IPU study, it was not possible to achieve objective 4; reasons for this are explored in the 'Limitations and Weaknesses' section, below. Nonetheless, this thesis establishes a framework for future studies designed to address these objectives more rigorously.

**Content Analysis Review**

Overall, this work highlighted the lack of research on mobile apps and particularly the lack of apps scientifically validated for preventing or intervening on the underlying causal and maintaining mechanisms of PPU. Existing mHealth solutions appear to be either overly strict (e.g., blocking all sexual content) or too passive (e.g., just providing an abstinence counter), with no clear middle ground. Notably, there appeared to be no option for dynamic self-regulation based on past behaviours. This led me to an idea for a future app based on behavioural posology: a dynamic content-blocking app that provides more nuanced control over pornography use. By incorporating a self-managed EMA, the app could become a just-in-time adaptive intervention with an EMA component, using EMA data to help users manage their behaviours adaptively.

As an example of how this could work, members of Sex Addicts Anonymous (SAA) are taught the 'three circles' framework, in which behaviours are categorised within different zones: the inner circle, representing compulsive, addictive behaviours they are trying to stop; the middle circle, which includes warning signs or activities that can lead to relapse; and the outer circle, which contains healthy behaviours and practices that support recovery (Fernandez et al., 2021a). Similarly, in Sex and Love Addicts Anonymous (SLAA), these are referred to as 'bottom line', 'middle line', and 'top line' behaviours (Fernandez et al., 2021a). One way this framework could be integrated into a dynamic content-blocking app is by allowing users to categorise their own online behaviours into these three circles, setting personalised boundaries for what content should be blocked depending on which zone their behaviour falls into. At the same time, users can perform a self-managed EMA, recording variables such as their mood, anxiety, stress, and sexual cravings multiple times per day. If the app detects increasing craving levels that suggest an impending bottom line behaviour (i.e., pornography use), it could prompt users to reduce middle line behaviours, such as browsing social media, and engage in top line behaviours, such as taking a walk or making an outreach call to another member of SAA or SLAA. Hence, such an app could combine content blocking with both a just-in-time adaptive intervention component and an EMAcomponent. Insights from this approach could also help users recognise patterns that lead to pornography use, making the self-reported EMA a potential tool to break the cycle of compulsive behaviour. Furthermore, this method could be applied to self-regulation of other digital habits, such as social media, online gaming, or general Internet use.

### *Content Blocking Applications*

While several of the app features presented in Chapter 3 provide ways to resist temptation to use pornography, the high popularity of content blocking apps suggests that there is a strong market demand for applications that can eliminate this temptation entirely. It is an open question as to whether digital self-control tools with content blocking features are more effective than other tools at reducing PPU, since apps that help users build resistance to pornography use may offer greater long-term benefits compared to those that merely block content, bypassing the person's development of self-control. However, content blocking apps have clear utility for certain populations. For example, they may be used to help reduce pornography exposure to minors, who are more susceptible to the harms of such content (Perez et al., 2017). Marshall and Miller (2024) found a significant relationship between age of first exposure to pornography, type of first exposure, and PPU in young adulthood, suggesting that some level of content restriction for minors is necessary. By using a broad-spectrum content blocker, parents can regulate a significant portion of sexual content with minimal effort. However, adjustments may be needed for certain social media platforms, which can contain large volumes of borderline pornographic (and explicitly pornographic) content (Coletto et al., 2017). Rofarello and De Russis (2021, p. 1) found that most digital self control toolss implement “a single-device conceptualization that poorly adapts to multi-device settings”, meaning that the choice of digital self control tool is crucial for this strategy’s success. Additionally, calibrating the strength and number of features is important. As an example, Lyngs et al. (2022) performed a content analysis of online reviews for generic digital self control tools, and found that content blocking tools were criticized if they were either too weak (i.e., easy to override), or too strong (i.e., overly restrictive or punishing of bad behaviour), suggesting that there may be a ‘Goldilocks zone’ of optimal content restriction and feature provision that users find most effective.

**What is Behavioural Posology For?**

Although EMA data can indicate the timing of affective dynamics, analysing pornography use purely from longitudinal data without a theoretical framework is challenging due to the numerous possible temporal patterns of affect that could be present in the data. Thus, the behavioural posology paradigm – in combination with opponent process theory – offers a theoretical framework for hypothesizing and testing specific temporal dynamics associated with pornography use. In a broader psychological context, the behavioural posology paradigm provides a formal mathematical approach to studying the relationship between behaviours and the temporal dynamics they produce, allowing us to better understand their causal impact on mental health outcomes. It is my hope that this paradigm will allow us to develop a theory of optimality in behavioural psychopharmacology, such that we can identify the healthy limits of pornography use (and other pleasurable behaviours), leading to improved treatment recommendations for PPU.

Behavioural posology takes a systems-based approach to analysing and optimizing human psychology and treating psychopathologies. It views the human body and brain as interconnected systems with complex feedback loops, allowing us to better quantify the relationships between these systems, external inputs, and internal behaviours. This perspective can be explained using the metaphor of a pilot flying an aircraft. In this dynamic system, stable flight represents balanced mental health, weather conditions represent external life circumstances, and the plane's feedback loops are akin to emotional regulation mechanisms. Different pilots (individuals) are in control of different aircraft (their own personalities, affected by genetics, upbringing, and environmental factors such as past traumas), and must deal with varying weather conditions (life circumstances). In this metaphor, the wrong behavioural adjustments – akin to adjusting flight controls – can reduce emotional stability, especially if these behaviours are performed at high frequencies, which can lead to dangerous positive feedback loops (such as addiction)[9].

We currently lack quantitative tools for behavioural self-regulation through the complexities of modern life, especially considering the rapid pace of development of digital technologies. A just-in-time adaptive intervention with an EMA component could act as the pilot's 'cockpit instruments', providing real-time data and feedback for self-regulation and analysis of one's behaviours and their effect on mental state while also providing recommendations to counter dangerous behavioural patterns. Developing these psychological tools may help some individuals to maintain a stable 'flight path' in an increasingly turbulent digital environment. In essence, behavioural posology provides a quantitative framework to develop these tools. While this thesis demonstrates how such an approach can be applied to analyse one's pornography use, it is hoped that it can also be applied to other behavioural disorders.

***Exposure Analysis***

I chose the name 'behavioural posology' to emphasise how this paradigm relies on the concept of dosage to study the healthy (and optimal) limits of behaviours. This distinguishes behavioural posology from fields such as 'behavioural pharmacology', which focuses on the effects of drugs on behaviour (Thompson & Schuster, 1968), and 'exposure science', which examines the impact of harmful environmental agents on health (Lioy, 2010). Nevertheless, there are likely to be valuable insights from both fields that could be incorporated into the behavioural posology paradigm, particularly when applied to digital behaviours such as pornography use. For instance, there may be learnings from drug pharmacology that could be applied to the consumption of pornography, even though it is not a 'drug' in the traditional sense of the word. Moreover, by taking an exposure analytic approach, pornography could be conceptualised as a harmful environmental agent that requires exposure limits. In summary, one could say that as a field of study, behavioural posology partially intersects with behavioural pharmacology and exposure science while primarily focusing on analysing behaviours and their direct effects on emotional states.

In fact, as I discovered during the writing of this thesis, there may be an even simpler formal equation for exposure that may provide an alternative mathematical framework for

[9] In the case of an aircraft, an example of such a positive feedback loop would be 'pilot-induced oscillations', in which a pilot repeatedly overcorrects their control inputs in response to aircraft deviations, leading to oscillatory instability (McRuer, 1995).

behavioural dose, particularly in cases where a repeatable behaviour involves exposure to digital content, such as pornography or social media:

$$1)\ E = \int_{t_0}^{t_1} C(t)dt$$

in which exposure ($E$) is a function of concentration ($C$) and time ($t$), and can incorporate multiple discrete exposures within the time interval $[t_0, t_1]$ (Lioy, 2010). Thus, while the variables $Potency$, $Amount$, $Duration$ and $Frequency$ provide a way of quantifying individual doses (as demonstrated in Chapter 5), an alternative variable, $Concentration$, could be used in place of $Dose_{total}$ as a way of formally expressing total exposure to digital content. Hence, the combined learnings of exposure science and behavioural pharmacology could provide an additional level of mathematical formality to the concept of behavioural dose for digital behaviours.

***Neurohormonal Modelling of Opponent Processes***

The opponent process theory of pornography use relies on the assumption that there are neurohormonal effects underlying virtually all behaviours. We already know that sexual activity involves complex cycles of internal processes that lead to the release of neuromodulators like dopamine and oxytocin (T. H. C. Krüger et al., 2021). The literature indicates that in general, more substantial dopamine spikes result in increased tolerance to dopamine, and with repeated use, dopamine spikes diminish while tolerance increases, consistent with opponent process theory and allostatic theory (Volkow et al., 2011). It is also known that the strength of synaptic transmission decreases with repeated stimulation at high frequencies, a phenomenon known as ‘frequency-dependent synaptic depression’ (Galarreta & Hestrin, 1998). This reduction in efficacy can result from multiple mechanisms, including depletion of neurotransmitter vesicles, desensitization of receptors, and changes in ion channel properties. Repeated stimulation can lead to long-term depression of synaptic transmission, and a persistent decrease in synaptic strength; this plays a role in synaptic plasticity, essential for processes such as motor learning and memory formation (Massey & Bashir, 2007). Such high-frequency repetition of stimulation can also lead to voltage patterns that mimic the ‘standard pattern of affective dynamics’ (Solomon & Corbit, 1974) in areas of the brain such as the ventral tegmental area, albeit over much shorter timescales (see for example Angelo & Margrie, 2011; Chu et al., 2010; Huang et al., 2019; Lavian & Korngreen, 2019; Momin et al., 2008; Quilichini & Bernard, 2012; Schneggenburger & Forsythe, 2006; Tsodyks & Markram, 1997). Hence, it may be that similar patterns of neurotransmitter depletion over longer timescales are contributing factors to the b-processes observed in the IPU study.

It is possible that repeated pornography use encourages short-term dopaminergic reinforcement rather than long-term self-control and higher-order goal achievement, since the user learns that pornography use can produce pleasurable dopaminergic spikes that satiate their cravings in the short-term. Additionally, prolactin and oxytocin levels have been shown to spike following orgasm (T. H. C. Krüger et al., 2021). Dopamine and prolactin are antagonistic hormones, with prolactin promoting calm and lethargy, traditionally enhancing relationships by keeping partners close post-coitus (T. H. C. Krüger et al., 2021). However, with solo pornography use, these pair-bonding effects are absent, in theory leaving the user in a state of lethargy and low motivation due to decreased dopamine and increased prolactin levels.

Opponent process theory predicts a curvilinear dose-response relationship between pornography use and mental health outcomes, where low frequencies of use have minimal impact on mental health, but beyond a certain threshold, allostasis triggers a rapid decline in outcomes[10]. Hence, the opponent process model provides some explanatory power for several non-linear psychological phenomena and can be used to generate hypotheses for analysing other compulsive behavioural patterns with threshold effects. However, applying computational models to human psychology in silico will invariably rely on simplifications that don't capture real-world complexity. Experimental testing of these hypothesised models will no doubt reveal errors that should be used to improve the original opponent process model. Indeed, the IPU study already revealed one possible flaw in the model, showing that the opponent processes associated with mood and pornography use may be triphasic rather than biphasic, with a decrease in affect just prior to the a-process. Yet this may make sense in the context of a repeatable behaviour: when pornography is used at high frequency, the craving period prior to one episode of pornography use may overlap with the b-process from a previous episode of pornography use, which may partially resolve this discrepancy.

The opponent process model predicts phenomena like the development of habituation, the proportionality of both habituation and sensitization to behavioural frequency and intensity, plateaus in affect during sustained behavioural repetition, the development of apparent tolerance, and exponential decay of affect after stimulus cessation (Blumstein, 2016; Koob & Le Moal, 2001; Negus et al., 2010; Peper, 2009; Solomon & Corbit, 1974; Uribe-Bahamonde et al., 2019). Thus, opponent process theory is linked to the theory of habituation and sensitization as part of dual-process theory (Groves & Thompson, 1970; Uribe-Bahamonde et al., 2019). In fact, habituation and sensitization may be treated as two independent processes that, combined,

[10] This aligns with the hormesis and LWT models.

determine the strength of a behavioural response to repeated stimuli (Groves & Thompson, 1970). It could be inferred from the models created in the behavioural posology study that sensitization may be a form of a-process allostasis, in which a-processes repeated at a high frequency lead to greater a-process magnitude overall, while habituation is possibly a form of b-process allostasis. Further research should investigate the possible links between these phenomena within the context of behavioural disorders.

## IPU Study and EMA Methodology

### *Summary of Findings*

The Internet Pornography Use (IPU) study provided a degree of validation for the behavioural posology paradigm in that I was able to detect the presence of b-processes following pornography use with masturbation, using ecologically valid data. While the results from this study require further examination and replication, they suggest that pornography use produces negative after-effects that are exacerbated by moral incongruence. However, even individuals with low moral incongruence may experience some negative effects, though this is likely to vary by context. For example, a person who chooses to avoid intimate relationships might use pornography as their only sexual outlet without feeling guilt or shame. In contrast, a married person might find that pornography use reduces one's sexual desire towards their partner; even if they don't feel guilty about it in the moment, they may still find it has a negative impact on their relationship. Thus, moral incongruence towards pornography is a personal issue that each individual must address. We have made preliminary steps towards understanding these effects, but much work remains to understand further the impact of environmental and situational factors on the relationship between moral incongruence, pornography use, and mental health.

The issue of context applies to many of the variables that were measured. For example, the Bayesian model results for anxiety in the IPU study were mainly in favour of the null hypothesis of no effect for both low and high moral incongruence participants. This may be due to the complexity of the temporal relationships between pornography use and anxiety; in specific contexts, pornography use may relieve anxiety in the short-term but exacerbate it in the long-term; in other individuals, the opposite may occur. The hierarchical mixed-effects models in the IPU study may not have captured individual differences in these relationship structures. However, it is also possible that the association between PPU and anxiety is unfounded. A systematic review by Grant Weinandy et al. (2023) found that most research on anxiety and Compulsive Sexual Behaviour Disorder (CSBD) provided inconsistent results on the relationship between the two constructs, with largely cross-sectional data based on inconsistent methodologies, and very little longitudinal data. Hence, new methods might be needed for better accuracy.

The data on episode length may provide evidence for the ‘supranormal stimulus’ hypothesis, which suggests that pornography provides a form of sexual novelty that may be even more physiologically potent than sexual intercourse with a partner (Barrett, 2010; Hilton Jr, 2013). Several studies have shown how pornography can lead to escalating use patterns (Blinka et al., 2022; Fernandez et al., 2021b; Hanseder & Dantas, 2023; Ince et al., 2023, 2024; Palazzolo & Bettman, 2020). The advent of tabbed browsing (introduced in 2006) and high-speed broadband appears to have exacerbated this issue, allowing pornography users to escalate their usage in ways not previously possible (Hilton Jr, 2013; Ince et al., 2024). As possibly observed in the IPU study, some users often engage in extended sessions, referred to as ‘pornographic binges’, using multiple strategies to counteract desensitization, such as increasing usage (quantitative tolerance), exploring more stimulating genres (qualitative escalation), switching between stimuli (‘tab-jumping’), and delaying orgasm (‘edging’) (Ince et al., 2024). This underscores the importance of distinguishing between pornography-enhanced masturbation and masturbation by itself, as they may have different effects on mental health (Perry, 2020; Prause, 2017, 2019).

### *Navigating Methodological Challenges*

In practical terms, the online data collection process implemented during the IPU study was successful, although it faced some minor issues, especially during the pilot phase. Only two out of seven pilot participants completed the follow-up post-EMA survey. These surveys were helpful in that they identified a software bug in the SEMA3 app used for the EMA, which was resolved by the SEMA3 team prior to the exploratory study and led me to exclude one participant’s data from the study. However, I found that the collected post-EMA data was not useful for testing the primary hypotheses. For this reason, as well as high attrition in the pilot study and the redundancy of questions between the pre- and post-EMA surveys, I chose to eliminate the post-EMA survey in the second exploratory study.

Initially I intended to use the nlme package in R (Pinheiro et al., 2024; R Core Team, 2022) to perform statistical modelling. However, it became apparent that the nlme package was limited regarding the bounds that could be placed on model parameters. Thus, I ran into several modelling issues, including convergence problems, unreliable and unrealistic parameter estimations, and violations of regression assumptions, such as homoscedasticity and normality of model residuals. As discussed in Chapter 6, the choice of scale for the mental wellbeing variables provided clearly defined bounds on measures of different types of emotional affect, providing a basis for prior distributions that could be utilised in the models. Hence, I decided to switch to Bayesian modelling using the brms package in R (Bürkner, 2017), which improved model consistency and offered greater flexibility by allowing bounded priors, thus reducing the solution space that needed to be searched during model optimization. It also provided all the advantages of Bayesian statistics, such as the ability to incorporate prior information, better handling of parameter uncertainty, improved model flexibility and robustness, direct probability statements about parameters, and more intuitive interpretation of results compared to null hypothesis significance testing (NHST) (Bürkner, 2017; Etz & Vandekerckhove, 2016; Kruschke & Liddell, 2018; Wagenmakers et al., 2018).

One of the advantages of the behavioural posology paradigm is its ability to break down and formulate behavioural doses using the following parameters: $Potency$, $Amount$, $Frequency$, and $Duration$. However, measuring these in practice during an EMA can be challenging. In the IPU study, I could only measure approximate analogues of these variables. $Potency$ was gauged by the type of sexual activity, whether the user had an orgasm, and their highest mood score during the sexual episode. $Amount$ was determined by the length of the sexual episode, while $Duration$ was measured across the EMA period. $Frequency$, in particular, was challenging to measure as it varied for each participant throughout the EMA. This variability poses a problem for modelling since the impact of $Frequency$ is uncertain, especially when considering the lagging effects of prior pornography use. While the IPU study successfully implemented some aspects of the behavioural posology paradigm, more work is needed to refine this approach and ensure that the measured factors accurately represent the underlying neurohormonal processes produced by these behaviours.

The temporal component of EMA data offers significant advantages. Repeated within-person measurements allow researchers to achieve substantial power with a small sample size. Although the sample consisted of only 24 participants, it still provided enough data to detect and quantify significant effects and effect sizes, despite high attrition rates[11]. Another benefit is the ability to quantify timescales for the duration of affective fluctuations produced by sexual episodes. Standard correlational statistical methods cannot accurately determine the length of these side effects due to the lack of a temporal component in measurement. This challenge is not unique to pornography but extends to other behavioural studies, where determining the timescale of effects incurs many complexities, such as identifying correct behavioural representations and motifs to analyse, and determining the optimal frequency of measurement (Berman, 2018). Yet by using the data provided by an EMA in combination with the behavioural posology paradigm and hierarchical mixed-effects modelling, we can tentatively conclude that the most significant shifts in temporal dynamics produced by pornography use likely last for at least a few hours. This

[11] However, it's important to note that we did not perform power calculations for all tests in the exploratory study, so many findings should be interpreted cautiously as they require replication (as discussed in Chapter 6).

has implications for future studies on detecting behavioural allostasis: we can predict that pornography use is likely to become harmful if the time between episodes of use is shorter than the critical decay duration of the affective fluctuations observed. In other words, using pornography multiple times within a few hours may lead to more substantial allostatic effects than using it multiple times over several days. It may be possible to incorporate the frequency of prior pornography use into the hierarchical mixed-effects models to detect allostatic effects, although this is a task for future research.

***What is the Optimal Level of Moral Incongruence Towards PPU?***

The findings of the IPU study provide new insights into moral incongruence theory, particularly the temporal nature of guilt and shame associated with pornography use. If validated, the results in this study suggest that the intensity of these emotions tends to increase immediately before pornography use for people with high moral incongruence and spike after pornography use before gradually diminishing. This suggests that these spikes in affect may be alleviated by abstinence, at least temporarily if not permanently. These results support previous studies showing that moral incongruence is a moderating factor leading to PPU, which makes sense, as humans naturally strive to reduce unpleasant states of cognitive dissonance, guilt, and shame. Even if pornography use were biologically harmless, excessive use may still lead to moral incongruence if the person feels that their use is detracting from other activities they would like to perform. Since moral self-evaluation and self-awareness tend to be negative experiences if performed to excess (Csikszentmihalyi & Figurski, 1982), it is plausible that self-recrimination following pornography use could be a potential cause of depressed mood, among other conditions.

The current literature often emphasises the role that moral incongruence plays in PPU. Yet we must be careful before suggesting that harm is directly proportional to one’s level of moral incongruence for several reasons. Firstly, this perspective overlooks the reasons behind an individual's moral incongruence. People may feel morally conflicted about pornography because it conflicts with their goals for spiritual, mental, or personal development. As a case in point, Hoagland et al. (2023) identified 14 general themes for moral opposition to pornography, including religiosity, concerns about abuse, and disgust. This highlights the complexity and diversity of individual reactions to pornography use. Secondly, many individuals have deeply ingrained moral structures that give their lives meaning and purpose. Is this inherently negative? The findings from the IPU study indicate that those with high moral incongruence tend to use pornography for shorter periods, potentially allowing more time for alternative activities. This might be beneficial in certain cases, which leads to my final query: what if the relationship between moral incongruence and long-term mental health outcomes is non-linear, possibly following a hormetic pattern where no moral incongruence towards pornography is neutral, moderate levels are beneficial, but high levels are harmful? One can imagine that a moderate level of moral incongruence might induce a small amount of guilt that may help a person reduce their pornography usage without leading to excessive shame and self-criticism if they occasionally slip up. However, testing such a hypothesis will be challenging.

In addition, it is difficult to impute a ‘right’ level of moral incongruence for any individual, as this will be heavily driven by their religious and moral philosophy. Reid et al. (2016) identified a possible mechanism by which religious individuals may experience a reaction similar to the abstinence violation effect, where after breaking a rule in one’s moral code (e.g., abstinence from masturbation or pornography use), an individual may feel that further immoral behaviour is inconsequential because they perceive themselves to be already morally compromised (Curry et al., 1987). This ‘fall from grace’ mindset may lead to an escalation in behaviours that they deem irredeemable in the eyes of their religious doctrine. However, further research is needed to determine whether this tendency to give up following a lapse is significantly different between religious and non-religious individuals in recovery (Reid et al., 2016).

It seems tautological to state that reducing feelings of moral incongruence can alleviate the guilt and shame experienced by individuals with PPU. However, it is crucial to distinguish between moral incongruence itself and the resulting feelings of guilt and shame. If we again refer to the behavioural posology model, we can propose two main approaches to reducing these negative feelings: decreasing behavioural dose and frequency – for example, by using content-blocking apps or therapies such as cognitive behavioural therapy (Lotfi et al., 2021) – or reducing extreme levels of moral incongruence through therapies such as acceptance and commitment therapy (Twohig & Crosby, 2010). Both methods alone are incomplete solutions. Reducing behavioural doses abruptly may be extremely difficult or counterproductive in many cases, while lessening moral incongruence might encourage increased levels of pornography use without perceived consequences. Indeed, the IPU study found that participants with low moral incongruence tended to use pornography for longer periods than those with high moral incongruence.

Therefore, a more effective solution may be to pursue both goals simultaneously: reducing behavioural dose and frequency, while also moderating extreme moral incongruence to levels that still help individuals to regulate their behaviour. This also allows for pornography use to be a pleasurable, infrequent activity for those who don’t suffer from PPU, rather than treating it as a negative behaviour in all cases. By combining these strategies, one can take an intermediate position in the debate between the two opposing views currently in the literature: that pornography is inherently immoral and addictive and should be avoided at all costs; and that PPU is triggered by extreme moral positions toward it, which should be dampened. Perhaps both views are only partially correct, and the combination of these strategies is where the true optimum lies. It also allows us to take a multilayered, 'defence in depth' approach to protecting one's mental health, similar to the method of using a combination of app features to reduce pornography use, as mentioned in Chapter 3.

Some may argue that the simplest approach to eliminating PPU is to reduce exposure to pornography, which, on the surface, appears to be the safest option[12]. However, given the pervasive nature of sexual content online, achieving complete avoidance might be unrealistic. Therefore, tools that limit exposure whilst fostering mental resilience in individuals may prove to be most effective. Regardless of whether PPU should be categorised as an impulse-control disorder, an obsessive-compulsive disorder, or an addiction, both strategies mentioned above are likely to have a positive impact on mental health outcomes.

It turns out that these two strategies align with some of the more general strategies for reducing cognitive dissonance that have appeared in the literature over the years. McGrath (2017) reviewed seven dissonance reduction strategies that humans commonly use: attitude change, distraction and forgetting, trivialization and self-affirmation, denial of responsibility, adding consonant cognitions, changing behaviour, and act rationalization. Many of these are potentially detrimental to long-term wellbeing in specific contexts, such as trivialization or denial of responsibilities that should hold higher priority in one's life. However, when trying to reduce PPU symptoms, both attitude change (reducing excessive levels of moral incongruence) and behavioural change (reducing pornography use frequency) may have complementary benefits to one's mental health. A possible example of attitude change triggered by pornography use in religious individuals is illustrated by Perry (2017), who found that pornography consumption might contribute to feelings of religious doubt and lower religious salience, suggesting that these individuals may opt to change their attitudes to resolve the cognitive dissonance they experience from their pornography use[13]. However, this may have some negative consequences, such as undermining deeply held beliefs, generating confusion about personal values, or strained relationships with religious peers.

Taking a broader view momentarily, one can argue that human societies necessarily impose "the establishment of a social and moral order sui generis" (Durkheim, 1893, p. 21). While

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[12] Effectively, this is the 'via negativa' approach of eliminating unnecessary threats to one's mental health (Taleb, 2022).

[13] Presumably, this type of attitude change may also be induced by a number of other 'sinful' behaviours, although further research is required to confirm this.

the merits and drawbacks of this societal order are philosophical questions outside of the scope of this thesis, it is apparent that some level of self-restraint is essential for achieving significant goals that benefit both oneself and society (such as, I hope, the writing of this thesis). Comparing such tasks with more immediately pleasurable activities can undermine motivation to focus on larger goals. Therefore, moral incongruence concerning certain behaviours is likely to be beneficial, particularly when the behaviour is harmful to either the individual or to society. For example, taking a strong moral stance towards the use of a dangerously addictive drug like heroin is clearly beneficial for both individual and society. With less overtly dangerous behaviours, such as pornography use, the line is blurrier but still exists. Having moral incongruence about using pornography for several hours each day, to the detriment of one's personal relationships and productivity, seems reasonable. In the IPU study, some participants with low perceived moral incongruence used pornography for several hours at a time. This raises the question: is such use unhealthy, even if the individual feels no moral incongruence? Or could additional moral incongruence reduce their pornography use, thereby enhancing their productivity and overall wellbeing within a broader societal context? It's difficult to say, and partly depends on what the individual might be doing instead of using pornography.

It may be that by gathering sufficient EMA data to quantify this relationship between moral incongruence and long-term mental health outcomes, we could develop a simplified model to help clinicians identify healthy limits on pornography use for each individual. Such a model could eliminate the need for extensive EMA of the individual, requiring only the patient's level of moral incongruence to determine their No Adverse Effect Limit (NOAEL) for pornography use. The work in this thesis is just the start of achieving this goal.

***Qualitative Analysis***

Our qualitative results from the IPU study highlight the complex interactions between triggers leading to pornography use. For instance, many participants reported using pornography before going to sleep. There is growing concern over the negative effects of screen time and social media use on sleep (Boniel-Nissim et al., 2023; Levenson et al., 2016; Scott & Woods, 2019), which raises the possibility of a link between screen-based pornography use and poor sleep quality, especially when combined with social media or phone use before bed. One qualitative study found that a side effect of PPU was decreased motivation and energy (Palazzolo & Bettman, 2020), possibly due to sleep loss caused by pornography use. Yet in this study, it appears that many participants were using pornography as a sleep aid, which may have led to a conditioned reliance on it for sleep. It is possible that pornography can have both positive and negative impacts on sleep quality, depending on the context in which it is used.

Certain participants often exhibited specific trigger combinations leading to pornography use. For example, one participant reported 27 episodes of pornography use with masturbation during the EMA period, with 23 of these episodes attributed exclusively to trying to get to sleep. In contrast, another participant recorded 25 episodes with various triggers: loneliness (12 episodes), intrusive thoughts or dreams (5), tiredness (4), lying in bed (3), boredom (2), being on their phone (2), and stress (2). This shows how each person may be driven to pornography use differently. Future research should attempt factor or cluster analysis to identify patterns in the combinations of triggers different participants experience, as this may lead to further insights on the causal patterns contributing to PPU.

Furthermore, the potential links detected in the IPU study between pornography use, loneliness, and relationship disconnectedness suggest that reducing isolation and increasing social interaction may also aid in managing PPU. Social support networks could be a protective factor, helping individuals cope with urges and reinforcing healthier social behaviours. This aligns with the approach promoted by 12-step groups such as SAA and SLAA, which emphasise the importance of community support and accountability in recovery. Both programs advocate for regular group meeting attendance (also known as 'fellowship'), where individuals can share their experiences, build meaningful connections, and receive encouragement from peers facing similar challenges (Fernandez et al., 2021a). Members are encouraged to check in with each other through the use of 'outreach calls', while social support is also provided through sponsors – more experienced members who guide newcomers through the recovery process (Fernandez et al., 2021a). Hence, such groups may provide a structured and supportive environment that reduces isolation through peer connection, fosters accountability, and encourages sustained behavioural change. Still, further research is required on these groups to determine their effectiveness as a treatment for PPU, particularly when compared to alternative treatments such as acceptance and commitment therapy (Crosby & Twohig, 2016; Hayes et al., 2006).

## Limitations and Weaknesses

### *Modelling Dose-Response Relationships with the Opponent Process Model*

The opponent process model may be helpful in simulating behavioural disorders such as PPU, but caution is needed when applying it to drug addiction. Grubbs et al. (2022) found that moral incongruence is less predictive of substance addiction than it is for behavioural problems such as PPU or gambling addiction. The neurobiology of drug addiction is complex and varies for each drug, so significant modifications to the model may be necessary – particularly if other individual factors are taken into account, such as the personality traits of drug users, as well as their drug preferences and prior experiences (Terracciano et al., 2008).

This caution is also essential when applying the generic model to other mental states. For example, while anxiety is regularly linked to depressive disorders (Spek et al., 2007), the evidence from the IPU study does not clearly establish a relationship between hedonic states and anxiety in the context of pornography use. Consequently, the pharmacodynamic parameters for anxiety are likely to differ from those associated with purely hedonic states. Moreover, the degree to which moderating variables such as moral incongruence predict the b-process amplitude for any behaviour will depend on the type of behaviour, and as such, the opponent process model must be adjusted for each type of behaviour.

The initial plan in the behavioural posology study was to model the dose-response relationship between pornography use and mental health metrics to test whether low doses of pornography use can be healthy for certain individuals in the hormetic sense. However, my initial proposed approach of integrating hedonic states over time is probably insufficient for modelling the nuances of individual psychological responses, as it only provides a unidimensional measure of the costs and benefits of pornography use. With more resources, a comprehensive study should consider multiple measures, including eudaimonic state – a separate construct from hedonic state that assesses one's meaning and purpose in life (Disabato et al., 2016) – as well as other variables such as economic utility, both in the short- and long-term. The challenge lies in creating a holistic model that includes all important variables while excluding those that complicate understanding and interpretation for future researchers.

To some extent, the opponent process model of PPU presented in the behavioural posology study simplifies reality in the short-term and contradicts some observational data for habituation and sensitization over the long-term. For example, the model does not account for the finding that "repeated series of habituation training and spontaneous recovery result in progressively more habituation" (Groves & Thompson, 1970, p. 240). It also falls apart at extremely high frequencies, causing a shift from negative to positive allostasis due to the summation of repeated a-processes that is unlikely to be realistic for most behaviours. Yet perhaps the greatest weakness of this model is that it does not account for random changes in behavioural frequencies or potencies, which are both factors that have an impact on sensitization, habituation, tolerance and allostatic rates (Chou & D'Orsogna, 2022; Peper, 2009). The simulated allostasis in the behavioural posology study was produced using constant behavioural frequencies and potencies, which ignores the inherent randomness of real-world scenarios. This limitation makes it difficult to assess whether a person's pornography use can be maintained at a healthy level based on the EMA analysis I performed, since the data displayed plenty of evidence that participants' behavioural frequencies fluctuate in unpredictable ways. Thus, further research is needed to improve the accuracy of the opponent process model and make it more robust to such edge cases. Otherwise, it may be that the model in its current form is better suited to analysing the short-term outcomes of binge pornography use – in other words, periods of high-frequency use concentrated within a limited timespan.

### *Weaknesses of the IPU Study*

#### Limitations of Causal Inference

Caution is required when interpreting any causal conclusions from the IPU study, which has some aspects of internal validity that need to be addressed. Reporting bias is always a potential issue with this type of ecological study, as participants may have misreported their pornography use, particularly if feelings of guilt influenced their responses. If this bias is present, it is likely to manifest as an under-reporting of one's frequency or length of pornography use or masturbation. Further, the effects of data truncation in the IPU study warrant further exploration, as its application appeared to influence the outcomes of the Bayesian models used, indicating that the removal of data beyond a certain cutoff may exclude certain elements of temporal dynamics from the final model. There is also the possibility that the frequency of data collection was too low to reliably detect true causal effects[14]. Yet at minimum, the detection of a b-process following pornography use – if confirmed by future research – would strongly suggest that pornography use lies somewhere in the causal chain of events leading to negative mental health outcomes in PPU sufferers.

Within-subject data can never fully establish causal relationships due to the possibility of confounding variables (Rohrer & Murayama, 2023). This applies here, as pornography use was observed rather than randomised in the IPU study. The behavioural posology approach is also best at capturing first-order effects rather than lagged or reciprocal effects, which may be better accounted for by a random-intercept cross-lagged panel (RI-CLPM) model that partially controls for unobserved confounders  (Hamaker et al., 2015; Rohrer & Murayama, 2023). However, the strength of the behavioural posology approach lies in its ability to model repeatable, discrete events and their effects on the dynamics of other variables, which is more difficult to achieve with CLPM-based methods due to their focus on regular time intervals and continuous variables, making them less suited for capturing the immediate and irregular impact of discrete events such as pornography use (Kuiper & Ryan, 2018).

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[14] However, this issue is likely mitigated by the aggregation of participant data, since survey responses occurred at varying times relative to sexual episodes.

### Limitations of Validity

Various constraints also limit the external validity of the IPU study. The sample was entirely self-selected, raising the possibility that some participants may have chosen not to participate due to their moral or religious beliefs, which could correlate with higher degrees of moral incongruence. Self-report bias is always a risk with this type of study, as participants may not accurately report all instances of sexual episodes – particularly if they feel increased guilt or shame around these episodes. Given current limitations in real-time assessment of emotional states in naturalistic settings, however, self-report remains the most feasible method available. Additionally, the sample, drawn from flyer respondents at AUT University along with the r/pornfree subreddit, may not represent the global population, reducing the generalizability of the findings. A more diverse and larger sample that includes participants from a broader range of backgrounds would be necessary to strengthen external validity in future research.

There are also concerns about the construct validity of some of the measures used in this study. Most of the daily EMA questions were specifically tailored for this study, and used a 0-10 Likert scale to capture affective states in the present moment (e.g., “On a scale of 0-10, how anxious do you CURRENTLY feel? 0 = no anxiety, 5 = moderate anxiety, 10 = extremely high anxiety”). Such questions have been employed in a similar fashion in several other studies on momentary emotions, supporting their construct validity. Furthermore, the choice of wording was necessary to capture temporal dynamics at high measurement frequency, and the variables and scales chosen were generic, having all been examined in different contexts elsewhere in the literature (Hall et al., 2021). However, some items, such as those assessing participants’ moral incongruence related to sexual activities (e.g., “I believe that pornography use is morally wrong”, measured on a scale of 0 [not at all] to 6 [very strongly]), have been less extensively studied. While these questions have been based on prior measures with strong face validity (Grubbs, Exline, et al., 2015; Grubbs, Kraus, et al., 2019; Lewczuk et al., 2020), these items have not undergone formal validation in this context, which may limit the generalizability of the findings. Given that this is a relatively nascent and rapidly evolving field of study, many of these approaches still require systematic validation.

Still, the convergent validity of certain variables may need to be assessed in future research. For example, accurately measuring one’s ‘highest level of mood’ retrospectively following a sexual episode may have been challenging for participants due to possible ambiguity in the phrase. This may reduce the perceived accuracy of the a-process peaks shown in Figure 17, in turn limiting the precision of the opponent process models derived from participants’ mood scores. A more objective measure of a-process magnitude, less dependent on subjective interpretation, might improve accuracy in future studies. Moreover, certain measures, such as the ‘relationship connectedness’ variable, may have been too vague and could benefit from being split into more specific variables to improve discriminant validity. The wording chosen for the relationship connectedness question (i.e., “AT THIS MOMENT, how emotionally connected do you feel to your loved ones?”) was designed to simultaneously capture participant’s feelings of emotional connectedness to their romantic partners, family members, and friends, without needing to specify who they felt most connected to. This concise measurement approach was also chosen to reduce participant response burden. However, future research could refine this by separating the construct into distinct measures for partners, family, and friends to enhance discriminant validity and provide more detailed insights into each type of relationship.

One of the initial assumptions of the IPU study was that state variables from the EMA (such as loneliness) could be compared with the corresponding trait variables from the pre-EMA survey (i.e., trait loneliness as measured by the ULS-8). Most of my analyses focused on relative measurements of state variables to quantify temporal dynamics, so the equivalence of state and trait variable measurements was unnecessary. Relative measurements also allowed for more objective assessments of personal emotional experiences, which are inherently subjective (Csikszentmihalyi & Figurski, 1982). However, this made integrating pre-EMA survey results with the EMA data more challenging. Additionally, it was difficult to determine the impact of using the PPCS-6 scale for measuring PPU; other scales, such as the CSBD-7 and CSBD-19, may have aligned more with recent diagnostic criteria in the ICD-11 (Bőthe, Nagy, et al., 2023). Alternatively, for studies focusing on perceived addiction or moral distress, the Cyber-Pornography Use Inventory (CPUI) may be more appropriate in future studies due to its focus on online pornography addiction (Grubbs et al., 2010; Grubbs, Volk, et al., 2015). Nevertheless, the PPCS-6 is widely regarded as an accurate assessment of PPU levels due to its balance between assessing behavioural patterns and psychological impacts, while being concise and easy to complete (Bőthe, Tóth-Király, Demetrovics, et al., 2020; Bőthe, Tóth-Király, Zsila, et al., 2017).

### Data Quality and Funding

EMA studies generally face several data quality issues that are hard to control, such as poor participant compliance, the potential for absurd data (i.e., data that does not make logical sense, repetitive responses to Likert scale questions, or nonsensical input in open fields), high rates of missing data, and selection bias against participants with cognitive disorders who may struggle with survey instructions (Lukasiewicz et al., 2007). The compliance rate of the IPU study was low (between 25%-29%), and the impact of pseudo-compliance and absurd data remains unclear, while selection bias is always a potential concern. Additionally, my measurements for episode length and mood during episodes were based on retrospective recall, which may be less accurate than the immediate EMA measurements used for other mental health variables.

Nonetheless, I believe that an EMA is currently the only plausible, feasible method for accurately capturing the temporal dynamics of real-life pornography use outside of a laboratory setting.

Due to time and resource limitations, I set the EMA period to one month only, which was insufficient for accurately measuring a homeostatic baseline for each participant's mental health variables. Such a baseline would have been necessary for quantifying temporal dynamics on an individual level. Hence, measuring at the sample level introduces significant uncertainty about the affective baseline for each participant. Additionally, although the IPU study data included a wide range of moral incongruence values, the dataset lacked participants at the extreme ends of the distribution, especially those with zero moral incongruence towards pornography use. This limited my ability to generalise the opponent process model to people at the extreme ends of the moral incongruence spectrum. Thus, there remains some uncertainty about the exact nature of moral incongruence as a moderating variable on the relationship between pornography use and mental health at these extremes.

A longer EMA period would offer greater modelling accuracy but introduces additional methodological challenges and potentially higher attrition rates. Moreover, it doesn't entirely solve problems such as confounding variables and determining appropriate measurement timescales. Affective states fluctuate over time, both in the short- and long-term, and are impacted by external life events; thus, every person's psychological state is influenced by a causal network unique to their life and environment. This overdetermination means that there is insufficient data to account for all possible individual variations in affective decay patterns, regardless of the length of EMA performed. It also limits our ability to determine the correct model of affective decay with complete confidence. Consequently, I simplified the approach for the IPU study, using an exponential decay model and testing only for moral incongruence as a moderating factor. However, each individual brings a unique set of external factors, making it extremely complex to understand their unique profile of temporal dynamics – a task far beyond the scope of the IPU study. It is also possible that the temporal resolution of the EMA was too coarse to detect rapid fluctuations in temporal dynamics. However, by aggregating pre- and post-episode affective scores across multiple sexual episodes, I ensured that the timing of sexual episodes was effectively random with respect to the EMA survey prompts. This design resulted in a higher effective sampling frequency across participants and episodes, thus partly mitigating the limitations in detecting high-frequency fluctuations.

When quantifying the effects of pornography use, it is important to control for masturbation, as the two activities may be performed either together or separately, with different effects (Perry, 2020; Prause, 2017, 2019). In addition, the context in which masturbation is performed is likely to have an impact on the valence of impact on mental health. For example, mutual masturbation has been linked to higher overall sexual satisfaction in couples (although it is also linked to lower sexual self-esteem), while solo masturbation is not associated or negatively associated with overall sexual satisfaction (Kılıç et al., 2023; Miller et al., 2019). It has also been suggested that masturbation, rather than pornography use by itself, may be a key factor in reduced relationship satisfaction, particularly once gender differences are accounted for, since men are more likely to masturbate in isolation (Perry, 2020). Unfortunately, due to sample size limitations, I was unable to fully control for masturbation in the IPU study, meaning that further research will be required to separate out the temporal dynamics of pornography use and masturbation, respectively.

Another challenge was the limited funding available for the IPU study, which required me to conduct the exploratory study without providing cash prizes to participants, due to uncertainty about expected participant numbers. However, there are alternative options for situations with limited funding that could have been used. Using a lottery to award a prize to EMA participants has shown promise in other studies to improve recruitment and adherence. A three-sample study by Harari et al. (2017) found that compliance rates were low for students who only received course credit (32.8%) but high for those who received money (76.7%) or the offer of a prize to randomly selected participants (71.4%). Therefore, offering a prize may produce similar compliance rates to cash rewards and is logistically simpler, requiring fewer payments to be processed. However, such an approach could be considered unethical due to the high time burden placed on participants performing an EMA; therefore, I decided to reward all participants equally in the IPU study[15].

Given the scope of the dataset and the study's focus on moral incongruence, I chose to exclude a whole-group analysis and instead focused on the primary research question: whether moral incongruence moderates the relationship between pornography use frequency and mental health outcomes. The results support this focus: the significant differences in b-process parameter magnitudes between high and low moral incongruence participants suggest that a whole-group analysis would have obscured important variation within the model. Future research with larger samples should revisit whole-group effects, but with a focus on exploring whether a continuous model can be developed linking moral incongruence to the magnitude of b-process parameters, and whether this model offers a significantly different perspective compared to whole-group analysis.

[15] It is also plausible that some participants joined the IPU study in the hopes that it would provide an external source of motivation to reduce their pornography use.

## Future Research and Applications

### *The Potential Applications of Behavioural Posology*

In a sense, behavioural posology seeks to reconcile the top-down approach of behavioural psychology with the bottom-up methodology of cellular neuroscience in understanding human behaviour. Behavioural psychology primarily examines observable behavioural outputs in response to stimuli, often treating the brain as a complex system or 'black box' without extensively exploring its internal mechanisms. In contrast, cellular neuroscience investigates how complex interactions between groups of neurons can give rise to behaviours. By using behavioural posology, coupled with sufficiently accurate models of both the underlying cellular processes and their psychological outputs, we can enhance our comprehension of the interplay between psychological processes and neural mechanisms. In the case of PPU, behavioural posology provides a mathematical formalism that may enable us to link the temporal dynamics produced by behaviours to their underlying neurophysiological phenomena, such as dopaminergic depletion. This approach offers a more comprehensive understanding of the links between stimuli, neurochemistry, and behaviour, presenting a valuable research avenue for exploring the causal mechanisms of addiction from an integrated systems perspective.

There is a growing volume of high-dimensional psychological data that, up until now, has largely been used for correlational studies. However, there is much still to be done regarding the longitudinal analysis of causal behavioural pathways leading to mental health disorders such as depression. Behavioural posology represents an attempt to formalise a system that can use the latest advances in processing high-dimensional data to extract better causal inferences about behavioural addictions and compulsions. By incorporating temporal and frequency-based components, we can determine which events precede others, allowing us to infer directional effects and, therefore, Granger causality (Granger, 1969). This method, though challenging and complicated by the curse of dimensionality – especially with the addition of a temporal dimension – is becoming more feasible with the latest rapid advances in machine learning and other statistical techniques. This may also open the door to performing an integrated study that combines EMA data with repeated-measures fMRI data, investigating the neural correlates and temporal dynamics of PPU sufferers simultaneously. Such a study could provide invaluable insights into key fMRI markers that may have diagnostic or prognostic value for determining the most appropriate method for treating PPU.

It is possible that with further development, behavioural posology combined with EMA data could be used under clinical guidance to determine safe behavioural dose limits for individuals, based on their unique genetics, history, and environmental factors. This technique could apply to pornography use as well as other behaviours, particularly gambling, gaming, or

Internet and social media use. By estimating individual a- and b-process parameters for a PK/PD model of pornography-induced opponent processes, we may provide a generalizable framework that can be adjusted for other behaviours. This framework could then support comparisons of b-process allostasis both within and across individuals and behavioural disorders. The approach also holds strong transdiagnostic potential, in that identifying aberrant temporal dynamics in one problematic behaviour could facilitate detection of similar patterns in other behaviours. This would then enhance the identification of shared mechanisms for therapeutic targets across disorders.

Notably, a self-managed EMA for managing problematic behaviours shares similarities with other clinical strategies, such as thought diaries used in cognitive behavioural therapy and diary cards in dialectical behavioural therapy, as both methods involve the systematic tracking of thoughts, emotions, and behaviours over time (Lotfi et al., 2021; Lungu & Linehan, 2017). This potentially makes the self-managed EMA a natural extension of existing strategies, allowing the patient to self-monitor their affective patterns in relationship to their problematic behaviour. Ideally, this would promote both improved self-awareness and greater capacity for real-time self-regulation. For example, an app capable of modelling the typical b-process trajectory following a problematic behaviour could also predict when the patient's behavioural frequency is going to lead to mental health problems due to b-process allostasis, and alert them as such.

The opponent process model predicts that pornography use may lead to hedonic allostasis due to repeated b-process buildup. Testing this hypothesis would require a longer EMA study to examine if different frequencies of pornography use produce varying additive b-process dynamics based on prior usage. In its current form, the opponent process model predicts that increased behavioural frequencies should lead to changes such as an increased initial decay rate of the affective b-process. However, this is speculative. Many challenges remain, including measuring a reliable homeostatic baseline for individual participants' mental health variables. Yet determining whether allostasis exists could be a key step in determining causal pathways leading to PPU. It may also provide a valuable quantitative marker for a mobile app designed to track users' affective states regarding pornography use. For example, an app that is able to detect harmful rates of allostasis could provide feedback that alerts the user when their frequency of pornography consumption appears to be having a negative effect on their mental health.

### *Regulation of Artificial Intelligence Algorithms*

In the process of developing behavioural posology, I realised that while the paradigm was a powerful tool for capturing the temporal dynamics of behaviours, it could also be used in reverse: our understanding of temporal dynamics could in turn be used to help individuals automate the regulation of their own behaviours. So, as a side project, I attempted to apply behavioural posology to the regulation of recommendation algorithms – a particular type of machine learning algorithm designed to tailor content that the user most wants to view online. These algorithms are prone to 'echo chamber' effects, in which a user's beliefs and content consumption preferences are reinforced by repeated, selective exposure to a limited subset of online content (Avin et al., 2023; Cinelli et al., 2021; Currin et al., 2022; Ge et al., 2020; Interian et al., 2023). To counter this dynamic, I programmed a regulator in the form of a code wrapper for recommendation systems, using allostatic opponent process theory within the behavioural posology paradigm to combat these echo chamber effects. When applied to a K-Nearest Neighbours machine learning algorithm, this approach was shown to be able to dynamically restrict harmful online content recommendations based on a user's recent browsing history. To validate this approach, I programmatically simulated a scenario in which the regulator was used to dynamically restrict a particular genre of potentially anxiety-provoking films that were present in a movie recommendation system. The result of this work was an article titled 'Reducing Echo Chamber Effects: An Allostatic Regulator for Recommendation Algorithms' (N. I. N. Henry et al., 2025)[16].

At the same time, large language models (LLMs) such as ChatGPT were being introduced worldwide, causing significant concern about the pace of development of artificial intelligence, or AI (Chen, Zaharia, et al., 2023; Rozado, 2023). I began to realise that there was potentially an even more powerful, second application – applying behavioural posology to not only the regulation of human behaviour, but also to the behaviour of AI agents in general. As concerns about AI safety were becoming increasingly prevalent in both the literature and in mainstream media (Irving & Askell, 2019), it became apparent that there was a lack of regulatory tools available for restricting potentially harmful, repeatable AI behaviours.

As discussed above, the combination of hormesis and opponent process theory provides a model in which the healthy limit of repeatable behaviours can be more accurately defined. This provided an opportunity to create a general-purpose regulatory framework based on the behavioural posology paradigm that could be used for AI behaviour classification and regulation. I identified that this could be used to potentially solve the value-loading problem for repeatable behaviours, which involves aligning AI systems with human values and preferences (Bostrom, 2014a). To address this, I developed HALO (Hormetic ALignment via Opponent processes), a regulatory paradigm based on hormetic analysis and behavioural posology. In this paradigm, AI

[16] For more information on this approach, the preprint for the paper 'Reducing Echo Chamber Effects: An Allostatic Regulator for Recommendation Algorithms' can be found at https://doi.org/10.1080/29974100.2025.2517191.

behaviours are modelled as opponent processes, which allows for a modified version of BFRA to quantify safe and optimal limits for AI behaviours. HALO offers a potential solution to AI safety dilemmas such as the 'paperclip maximiser' scenario, in which an AI is incentivised to create as many paperclips as possible, but ends up destroying humanity in its blind quest to do so (Bostrom, 2014a, 2014b). The article resulting from this research was called 'A Hormetic Approach to the Value-Loading Problem: Preventing the Paperclip Apocalypse?' (N. Henry et al., 2024), and is also currently under review[17].

I chose not to include these two papers in this thesis as they fall outside the scope of treating PPU, which was the original focus of this work. However, both papers are applications of behavioural posology, applied in the broader context of online content and AI regulation. Hence, they each demonstrate the paradigm's potential to address complex regulatory challenges in the modern world of digital technologies and AI. While these approaches are still theoretical and require further validation in real-world environments, they represent promising research avenues for managing emerging ethical and practical concerns in our rapidly evolving technological landscape.

***The Role of Guilt and Shame in PPU***

Guilt and shame are often treated as separate constructs. Miceli and Castelfranchi (2018) argue that guilt suggests a negative *moral* self-evaluation that focuses on the morality of one's behaviours, while shame suggests a negative *nonmoral* self-evaluation, often involving a negative evaluation of the entire self, emphasizing personal inadequacy relative to an ideal self. Research by Tangney and Dearing (2002) suggest that guilt is the more valuable of the two constructs, being more action-oriented and leading to reparative behaviours, whereas shame is self-focused and can result in withdrawal and feelings of worthlessness. Yet differentiating between these two constructs in a research context remains challenging.

In the IPU study, the within-person correlation between guilt and shame was so strong that treating them as a single merged construct was tempting. This complicates the differentiation between potential adaptive benefits from moral self-evaluation and maladaptive experiences such as depression and anxiety from excessive shame and self-criticism (Bhushan et al., 2020). Yet despite the observed correlation between guilt and shame, the Bayesian evidence supporting the exponential models was stronger for guilt than for shame. This may suggest that sexual guilt is a

[17] For more information on this approach, the preprint for the paper 'A Hormetic Approach to the Value-Loading Problem: Preventing the Paperclip Apocalypse?' can be found at https://doi.org/10.48550/arXiv.2402.07462.

more immediate, short-term experience felt in close proximity to sexual behaviour, while sexual shame is a more persistent experience that lingers in the background long after pornography use has ended. Further research is needed to test these hypotheses.

One aspect not addressed in the IPU study was the type of pornography participants viewed. By breaking down pornographic doses into the variables $Potency$, $Amount$, $Frequency$ and $Duration$, we can infer that different genres of pornography likely produce varying levels of $Potency$ that induced differing a-process and b-process magnitudes. For instance, softcore pornography may have lower $Potency$ than violent pornography, while erotic literature may produce entirely different effects to visual pornography. The genre used may also partially predict the intensity of guilt and shame one feels following pornography use. Although the IPU study did not explore these effects due to ethical constraints, it may be beneficial to include the type of pornography used as a variable in future research.

### *Can Pornography Use be Addictive?*

The decision to label a behaviour as addictive is highly dependent on one's definition of addiction, which is still heavily debated in academic circles. It has been suggested that the stigma associated with the 'addict' label may do more harm than good by changing the way people think about themselves and their relationships (Dover et al., 2024), and may also lead to increased feelings of guilt and shame that drive the individual to consume more pornography to alleviate these feelings. Another argument is that an individual's 'pornography addiction' may worsen because they believe they are addicted, rather than actually being caught in a true state of addiction in the neurochemical sense of the word.

Still, we must be cautious before being too conservative in our diagnosis of addiction. The academic and clinical debate as to whether PPU is an addiction, an impulse-control disorder, an obsessive-compulsive disorder, or even a disorder at all is certainly warranted, as there is much evidence on all sides. However, the nuances of this debate are likely to be lost on the general public, who may misinterpret this debate and use it to claim that pornography is harmless. Hence, the public must be educated on the risks of not just addictive behaviours but also compulsive and impulsive behaviours. Moreover, it is vitally important to determine clinically significant thresholds for PPU – in other words, identifying the NOAEL for pornography use for each individual. As demonstrated in Figure 21, the determination of these thresholds is an incremental process that improves in proportion to the completeness of our knowledge (Grandjean, 2016).

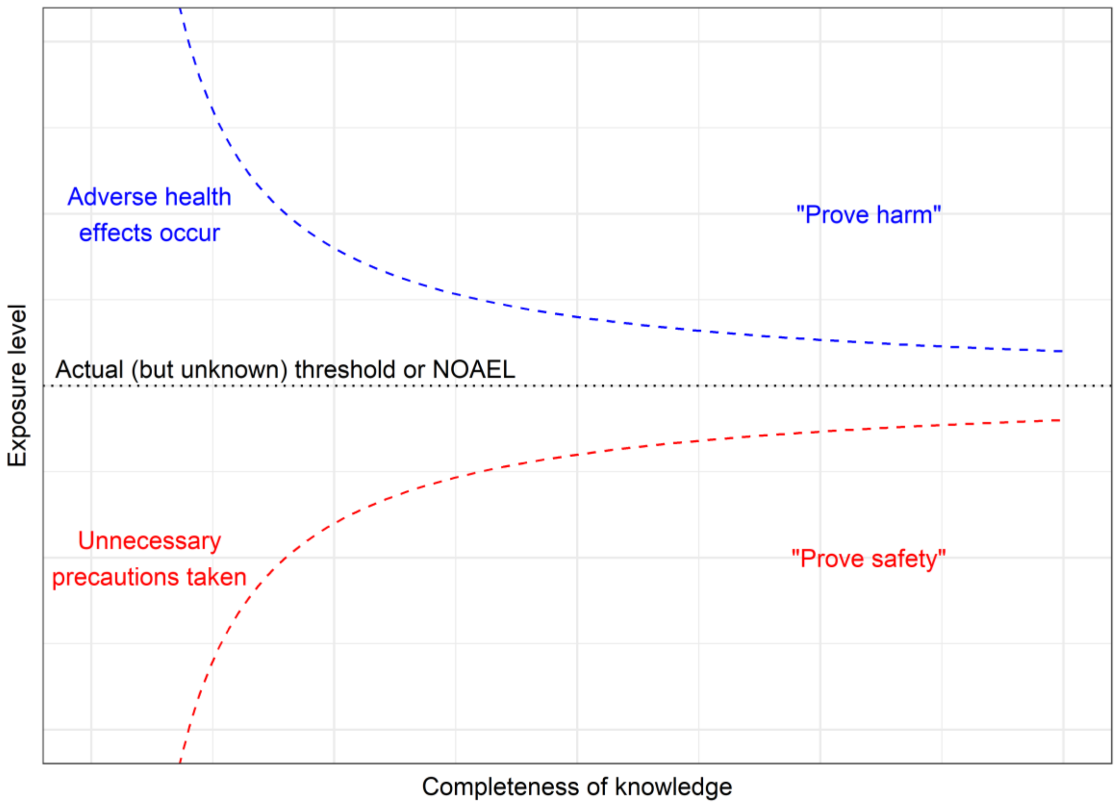


*Figure 21: Determination of the hormetic limit, or NOAEL, using an iterative scientific approach. As knowledge increases, the uncertainty of NOAEL decreases. Yet only with near-perfect knowledge will NOAEL be determined precisely. Until that point, low-level exposure may be permitted, but a conservative approach should probably be taken, in which the exposure level is kept low until evidence suggests that it is safe to increase it. Adapted from (Grandjean, 2016).*

One of the keys to determining whether pornography use can be addictive is testing whether abstinence results in short-term withdrawal symptoms that alleviate over time, such as depression or brain fog. There is research showing that pornography abstinence is generally associated with positive mental health outcomes in the long-term (Fernandez et al., 2021b, 2021a), including for members of the r/pornfree subreddit (Jenkins, 2018). Yet the effects of abstinence and withdrawal from pornography and masturbation in both the short-term and long-term remain poorly understood (Kraus et al., 2016). There also remain several reported phenomena that have not been adequately studied. For example, Fernandez et al. (2021b) found evidence of a 'flatline' – a period of decreased sexual desire and libido during abstinence, which was quite disconcerting for some participants. The flatline is commonly referenced by members of the r/NoFap community also, who claim that it is a temporary period of decreased sexual desire, reduced energy, low mood and emotional numbness that occurs for some people during their period of abstinence (*NoFap® Porn Addiction Recovery*, 2022).

In order to examine such phenomena, an abstinence study lasting several weeks (or longer) may be required, as one week is probably too short to capture all potential withdrawal and tolerance effects (Lewczuk, Wizła, et al., 2022). The maximum abstention period observed in the IPU study was 17.5 days between sexual episodes, although most participants used pornography every few days. In their analysis of the 'Reboot Nation' online abstinence forum, Fernandez et al. (2021) explored the potential benefits of abstaining from pornography for periods ranging from seven days to one year. Participants believed that abstinence helped 'rewire' their brains, reporting psychological benefits such as improved mood, increased energy, mental clarity, focus, confidence, motivation, and productivity. There were other benefits also reported, including social benefits such as increased sociability, improved relationship quality, and a greater sense of connection with others, while sexual benefits included a stronger desire for partnered sex and increased sexual sensitivity and responsiveness (Fernandez et al., 2021b).

However, many others found it nearly impossible to achieve abstinence over a full reboot period (Fernandez et al., 2021b). There was some evidence of this in the IPU study, as highlighted by a comment from one participant:

> "It's been 1 month today since I decided to quit porn. I've quit prior for almost 2 years. Basically, I started watching it again, but it would be once every two weeks or once a month. I just couldn't stop… I still crave porn, and I just think that quitting porn and masturbating is a lot harder than people think."

In fact, from Griffiths' six component model of addiction, at least four components (salience, mood modification, relapse and withdrawal) are all partly evidenced by the data in the IPU study, while the remaining two (tolerance and conflict) are implied. For example, the PPCS-6 contains questions demonstrating tolerance ("I felt that I had to watch more and more porn for satisfaction") and conflict ("When I vowed not to watch porn anymore, I could only do it for a short period of time") (Bőthe, Tóth-Király, Demetrovics, et al., 2020, p. 347), which many participants agreed with. One could also frame the moral incongruence questions as providing similar evidence of conflict and relapse.

It may be that trait changes in variables such as mood and anxiety can only be observed after a much longer period of attempted abstinence than what has previously been measured. However, an abstinence study is also necessary to understand how lapse rates change over time, particularly since the probability of lapse is likely to decrease as abstinence length increases (Sutton, 1979; Witkiewitz & Marlatt, 2007). Given that similar abstinence research has been performed on social media deactivation over one to four weeks (Allcott et al., 2020; Asimovic et al., 2021, p. 202), and the lack of research on abstinence from addictive behaviours in general (Fernandez et al., 2020), it seems prudent to conduct a long-term pornography abstinence study. Still, the longer the study, the greater the potential for decreased compliance and for the ‘downward drift’ phenomenon to occur, in which participants report progressively fewer negative affect-related symptoms following repeated testing (see Gilbert et al., 2019, p. 538) – an effect that was observed by Fernandez et al. (2023). This will need to be controlled for in future studies[18].

I propose that the ideal time to perform such a study would be during ‘No Nut November’, when thousands of people worldwide take on the challenge of abstaining from masturbation during the month of November. Despite the popularity of this event, there is virtually no research on it. Surprisingly, there is also very little research on the 90-day ‘Reboot’ period performed by members of the r/NoFap subreddit, during which members abstain from pornography, masturbation, or both (Chasioti & Binnie, 2021). The EMA method shown in the IPU study, with modifications, has the potential to assess the effects of long-term abstinence from pornography. Such a study could also include a content-blocking app as part of the intervention to evaluate its effectiveness in promoting abstinence. Furthermore, the study length does not need to be restricted to the month of November; it could also include the weeks both before and after November, which would provide valuable data for comparison purposes. Such a study may also provide some insights into the psychosocial effects of abstaining as part of a collective movement, rather than relying solely on individual willpower.

***Quantifying the Healthy Limit of Pornography Use***

The EMA data produced in the IPU study, combined with an accurate behavioural posology model of underlying pharmacodynamics, may be one path towards quantifying the healthy limit of pornography use in each individual. However, at a population level, it may be easier to quantify the within- and between-person relationships between the frequency of pornography use and the aggregated mental health scores for individuals over a defined period to determine the level at which pornography use has negative effects. Plots of these relationships can then be created in a similar fashion to those created by Przybylski & Weinstein (2017), who demonstrated a hormetic relationship between daily digital screen use and mental wellbeing that has since been replicated in other studies (Brannigan et al., 2023; Loban et al., 2024). One could statistically test for hormesis using the Mack-Wolfe test, a non-parametric rank test for detecting biphasic relationships (Deng et al., 2000). Achieving this would require a large-scale survey with a far greater sample size than the one I acquired. However, such a study would only produce correlational data; this would still need to be combined with longitudinal EMA data (or similar)

[18] A related hypothesis to test would be that this form of self-moderated EMA has similar effects to mindfulness meditation, where one observes their urges and affective states over time, and thus becomes more aware of them in a daily context, in turn affecting their results.

to show the causal mechanisms behind such a hormetic or Linear With Threshold (LWT) relationship if it exists. Combining these two types of studies would provide the greatest certainty in the healthy limit of pornography use. The hormetic and LWT models discussed in the behavioural posology study have broader implications for evaluating one's pornography use in a psychotherapeutic setting. Some individuals might maintain a stable relationship with pornography, where their usage remains consistent in type and frequency without escalating to more graphic content or increasing usage over time. If their usage does not negatively impact other areas of their life, it may be considered acceptable. However, how many people can genuinely claim this about their pornography use? The boundary between the level of pornography use in which the rewards exceed the costs and vice-versa is fuzzy. As mentioned above, the increasing $Potency$ of pornography being produced, combined with the advent of novel technologies such as AI and virtual reality, may significantly enhance its addictive potential. Therefore, developing a clear method for quantifying when pornography use becomes harmful will be crucial in the near future. If this information were to be integrated into a mobile app for treating PPU, it could provide individuals with a clear metric against which they may evaluate their pornography consumption, possibly helping them to determine whether they need to make changes in their life.

**Conclusion**

While several mobile applications exist that may provide useful features for people trying to reduce PPU, there remains a lack of research to quantify the effectiveness of any of these tools. Many of these apps claim to help users manage ‘pornography addiction’, even though there remains much debate about whether this is the right label to apply to the condition. Yet categorizing PPU is challenging in today’s research environment with current statistical and psychological methods, largely due to the lack of tools that can establish the causal nature of the relationships between pornography use and affective states.

Behavioural posology provides an alternative paradigm which one can use to model the temporal relationship between pornography use and mental health. In this thesis, I demonstrated that using EMA for longitudinal data collection within the behavioural posology paradigm provides a new understanding of the temporal dynamics of pornography use and masturbation, offering potential insights into the directionality of these relationships. If validated, the opponent process model of pornography use suggests that PPU treatments should combine two main strategies: reducing the frequency and intensity of pornography use, and moderating extreme levels of moral incongruence towards pornography use. To test this theory, I recommend conducting quantitative EMA studies on long-term abstinence from pornography to better understand its impact on mental health.

Ultimately, the goal of this thesis was to develop a framework for analysing the healthy limits of behaviours more broadly, in the hope that this method could be applied to other behaviours, particularly those involving digital content consumption. It is hoped that this research will provide fresh insights on the nature of PPU that will enable us to develop scientifically validated therapies for PPU and other behavioural disorders. In the meantime, more research and funding are required to aid the development of mobile applications for PPU treatment, to make them more adaptable to the momentary needs of individuals.

## References


Aboujaoude, E. (2019). Problematic Internet use two decades later: Apps to wean us off apps. *CNS Spectrums*, *24*(4), 371–373. https://doi.org/10.1017/S109285291800127X

Agaskar, A., & Lu, Y. M. (2013). ALARM: A logistic auto-regressive model for binary processes on networks. *2013 IEEE Global Conference on Signal and Information Processing*, 305–308. https://doi.org/10.1109/GlobalSIP.2013.6736876

Agathokleous, E., Kitao, M., & Calabrese, E. J. (2020). Hormesis: Highly Generalizable and Beyond Laboratory. *Trends in Plant Science*, *25*(11), 1076–1086. https://doi.org/10.1016/j.tplants.2020.05.006

Ahmed, S. H., & Koob, G. F. (2005). Transition to drug addiction: A negative reinforcement model based on an allostatic decrease in reward function. *Psychopharmacology*, *180*(3), 473–490. https://doi.org/10.1007/s00213-005-2180-z

Allcott, H., Braghieri, L., Eichmeyer, S., & Gentzkow, M. (2020). The Welfare Effects of Social Media. *American Economic Review*, *110*(3), 629–676. https://doi.org/10.1257/aer.20190658

Alleman, R. J., Katunga, L. A., Nelson, M. A. M., Brown, D. A., & Anderson, E. J. (2014). The “Goldilocks Zone” from a redox perspective—Adaptive vs. Deleterious responses to oxidative stress in striated muscle. *Frontiers in Physiology*, *5*. https://www.frontiersin.org/articles/10.3389/fphys.2014.00358

Allen, A., Kannis-Dymand, L., & Katsikitis, M. (2017). Problematic internet pornography use: The role of craving, desire thinking, and metacognition. *Addictive Behaviors*, *70*, 65–71. https://doi.org/10.1016/j.addbeh.2017.02.001

Amigó, S., Caselles, A., & Micó, J. C. (2008). A dynamic extraversion model. The brain’s response to a single dose of a stimulant drug. *British Journal of Mathematical and Statistical Psychology*, *61*(1), 211–231. https://doi.org/10.1348/000711007X185514

Anderson, D. J., & Adolphs, R. (2014). A Framework for Studying Emotions across Species. *Cell*, *157*(1), 187–200. https://doi.org/10.1016/j.cell.2014.03.003

Anderson, T., Petranker, R., Rosenbaum, D., Weissman, C. R., Dinh-Williams, L.-A., Hui, K., Hapke, E., & Farb, N. A. S. (2019). Microdosing psychedelics: Personality, mental health, and creativity differences in microdosers. *Psychopharmacology*, *236*(2), 731–740. https://doi.org/10.1007/s00213-018-5106-2

Andersson, C., Carlström, C., Amroussia, N., & Lindroth, M. (2024). Using Twelve-Step Treatment for Sex Addiction and Compulsive Sexual Behaviour (Disorder): A Systematic Review of the Literature. *Sexual Health & Compulsivity*, 1–19. https://doi.org/10.1080/26929953.2024.2339208

Andersson, G., Bergström, J., Holländare, F., Carlbring, P., Kaldo, V., & Ekselius, L. (2005). Internet-based self-help for depression: Randomised controlled trial. *The British Journal of Psychiatry: The Journal of Mental Science*, *187*, 456–461. https://doi.org/10.1192/bjp.187.5.456

Andrews, G., Cuijpers, P., Craske, M. G., McEvoy, P., & Titov, N. (2010). Computer therapy for the anxiety and depressive disorders is effective, acceptable and practical health care: A meta-analysis. *PloS One*, *5*(10), e13196. https://doi.org/10.1371/journal.pone.0013196

Angelo, K., & Margrie, T. W. (2011). Population diversity and function of hyperpolarization-activated current in olfactory bulb mitral cells. *Scientific Reports*, *1*(1), Article 1. https://doi.org/10.1038/srep00050

Asimovic, N., Nagler, J., Bonneau, R., & Tucker, J. A. (2021). Testing the effects of Facebook usage in an ethnically polarized setting. *Proceedings of the National Academy of Sciences*, *118*(25), e2022819118. https://doi.org/10.1073/pnas.2022819118

Atwood, J. D., & Gagnon, J. (1987). Masturbatory Behavior in College Youth. *Journal of Sex Education and Therapy*, *13*(2), 35–42. https://doi.org/10.1080/01614576.1987.11074907

Avin, C., Daltrophe, H., & Lotker, Z. (2023). *Breaking the Echo Chamber Effect in Social Media: An Impossibility Result*. https://doi.org/10.21203/rs.3.rs-3296371/v1

Ayres, M. M., & Haddock, S. A. (2009). Therapists' approaches in working with heterosexual couples struggling with male partners' online sexual behavior. *Sexual Addiction \& Compulsivity*, *16*(1), 55–78.

Barrett, D. (2010). *Supernormal Stimuli: How Primal Urges Overran Their Evolutionary Purpose*. W. W. Norton & Company.

Beal, D. J., & Weiss, H. M. (2003). Methods of Ecological Momentary Assessment in Organizational Research. *Organizational Research Methods*, *6*(4), 440–464. https://doi.org/10.1177/1094428103257361

Bechara, A., Bertolino, M. V., Casab, A., Munarriz, R., Goldstein, I., Morin, A., Secin, F., Literat, B., Pesaresi, M., & Fredotovich, N. (2003). Romantic partners use of pornography: Its significance for women. *Journal of Sex \&Marital Therapy*, *29*(1), 1–14.

Bedrov, A., & Bulaj, G. (2018). Improving self-esteem with motivational quotes: Opportunities for digital health technologies for people with chronic disorders. *Frontiers in Psychology*, *9*(OCT), 2126. https://doi.org/10.3389/FPSYG.2018.02126/BIBTEX

Berman, G. J. (2018). Measuring behavior across scales. *BMC Biology*, *16*(1), 23. https://doi.org/10.1186/s12915-018-0494-7

Berridge, K. C., & Kringelbach, M. L. (2015). Pleasure systems in the brain. *Neuron*, *86*(3), 646–664. https://doi.org/10.1016/j.neuron.2015.02.018

Berridge, K. C., Robinson, T. E., & Aldridge, J. W. (2009). Dissecting components of reward: 'Liking', 'wanting', and learning. *Current Opinion in Pharmacology*, *9*(1), 65–73. https://doi.org/10.1016/j.coph.2008.12.014

Bhushan, B., Basu, S., & Dutta, S. (2020). Revisiting Guilt, Shame, and Remorse. *Psychological Studies*, *65*(3), 247–260. https://doi.org/10.1007/s12646-020-00561-z

Biel, M., Wahl-Schott, C., Michalakis, S., & Zong, X. (2009). Hyperpolarization-Activated Cation Channels: From Genes to Function. *Physiological Reviews*, *89*(3), 847–885. https://doi.org/10.1152/physrev.00029.2008

Blinka, L., Ševčíková, A., Dreier, M., Škařupová, K., & Wölfling, K. (2022). Online Sex Addiction: A Qualitative Analysis of Symptoms in Treatment-Seeking Men. *Frontiers in Psychiatry*, *13*. https://doi.org/10.3389/fpsyt.2022.907549

*BlockSite: Easily block distracting websites and apps*. (2022). BlockSite. https://blocksite.co/

Blumstein, D. T. (2016). Habituation and sensitization: New thoughts about old ideas. *Animal Behaviour*, *120*, 255–262. https://doi.org/10.1016/j.anbehav.2016.05.012

Bobashev, G., Holloway, J., Solano, E., & Gutkin, B. (2017). A Control Theory Model of Smoking. *Methods Report (RTI Press)*, *2017*. https://doi.org/10.3768/rtipress.2017.op.0040.1706

Böhm, M., Franz, P., Dekker, A., & Matthiesen, S. (2015). Desire and dilemma – gender differences in German students' consumption of pornography. *Porn Studies*, *2*(1), 76–92. https://doi.org/10.1080/23268743.2014.984923

Bolanos, J., & Morgentaler, A. (2020). Successful treatment of Post-orgasmic illness syndrome with human chorionic gonadotropin. *Urology Case Reports*, *29*, 101078. https://doi.org/10.1016/j.eucr.2019.101078

Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computational Science*, *2*(1), 1–8. https://doi.org/10.1016/j.jocs.2010.12.007

Boniel-Nissim, M., Tynjälä, J., Gobiņa, I., Furstova, J., Eijnden, R. J. J. M. van den, Marino, C., Klanšček, H. J., Klavina-Makrecka, S., Villeruša, A., Lahti, H., Vieno, A., Wong, S. L., Villberg, J., Inchley, J., & Gariépy, G. (2023). Adolescent use of social media and associations with sleep patterns across 18 European and North American countries. *Sleep Health: Journal of the National Sleep Foundation*, *0*(0). https://doi.org/10.1016/j.sleh.2023.01.005

Borgogna, N. C., & McDermott, R. C. (2018). The role of gender, experiential avoidance, and scrupulosity in problematic pornography viewing: A moderated-mediation model. *Sexual Addiction \& Compulsivity*, *25*(4), 319–344.

Borgogna, N. C., Owen, T., Johnson, D., & Kraus, S. W. (2023). No Magic Pill: A Systematic Review of the Pharmacological Treatments for Compulsive Sexual Behavior Disorder. *The Journal of Sex Research*, *0*(0), 1–14. https://doi.org/10.1080/00224499.2023.2282619

Bos, F. M., Schoevers, R. A., & aan het Rot, M. (2015). Experience sampling and ecological momentary assessment studies in psychopharmacology: A systematic review. *European Neuropsychopharmacology*, *25*(11), 1853–1864.

Bostrom, N. (2014a). *Hail mary, value porosity, and utility diversification*. https://www.nickbostrom. com/papers/porosity.pdf

Bostrom, N. (2014b). *Superintelligence: Paths, dangers, strategies*. Oxford University Press, Oxford.

Bostwick, J. M., & Bucci, J. A. (2008). Internet Sex Addiction Treated With Naltrexone. *Mayo Clinic Proceedings*, *83*(2), 226–230. https://doi.org/10.4065/83.2.226

Botelho, A., Baker, R., Ocumpaugh, J., & Heffernan, N. (2018). *Studying Affect Dynamics and Chronometry Using Sensor-Free Detectors*. International Educational Data Mining Society.

Bőthe, B., Baumgartner, C., Schaub, M. P., Demetrovics, Z., & Orosz, G. (2020). Hands-off: Study protocol of a two-armed randomized controlled trial of a web-based self-help tool to reduce problematic pornography use. *Journal of Behavioral Addictions*, *9*(2), 433–445.

Bőthe, B., Baumgartner, C., Schaub, M. P., Demetrovics, Z., & Orosz, G. (2021). Hands-off: Feasibility and preliminary results of a two-armed randomized controlled trial of a web-based self-help tool to reduce problematic pornography use. *Journal of Behavioral Addictions*.

Bőthe, B., Koós, M., Nagy, L., Kraus, S. W., Demetrovics, Z., Potenza, M. N., Michaud, A., Ballester-Arnal, R., Batthyány, D., Bergeron, S., Billieux, J., Briken, P., Burkauskas, J., Cárdenas-López, G., Carvalho, J., Castro-Calvo, J., Chen, L., Ciocca, G., Corazza, O., … Vaillancourt-Morel, M.-P. (2023). Compulsive sexual behavior disorder in 42 countries: Insights from the International Sex Survey and introduction of standardized assessment tools. *Journal of Behavioral Addictions*. https://doi.org/10.1556/2006.2023.00028

Bőthe, B., Nagy, L., Koós, M., Demetrovics, Z., Potenza, M. N., International Sex Survey Consortium, & Kraus, S. W. (2024). Problematic pornography use across countries, genders, and sexual orientations: Insights from the International Sex Survey and comparison of different assessment tools. *Addiction (Abingdon, England)*. https://doi.org/10.1111/add.16431

Bőthe, B., Nagy, L., Kraus, S., Demetrovics, Z., Potenza, M., Michaud, A., Ballester-Arnal, R., Batthyány, D., Bergeron, S., Billieux, J., Briken, P., Burkauskas, J., Cárdenas, G., Carvalho, J., Castro-Calvo, J., Chen, L., Ciocca, G., Corazza, O., Csako, R., & Vaillancourt-Morel, M.-P. (2023). Compulsive sexual behavior disorder in 42 countries: Insights from the International Sex Survey and introduction of standardized assessment tools. *Journal of Behavioral Addictions*, *12*, 393–407. https://doi.org/10.1556/2006.2023.00028

Bőthe, B., Potenza, M. N., & Demetrovics, Z. (2024). Debates on Compulsive Sexual Behavior Disorder: A Call for Global and Interdisciplinary Perspectives. *Archives of Sexual Behavior*, *53*(4), 1215–1220. https://doi.org/10.1007/s10508-024-02836-2

Bőthe, B., Potenza, M. N., Griffiths, M. D., Kraus, S. W., Klein, V., Fuss, J., & Demetrovics, Z. (2020). The development of the Compulsive Sexual Behavior Disorder Scale (CSBD-19): An ICD-11 based screening measure across three languages. *Journal of Behavioral Addictions*, *9*(2), 247–258. https://doi.org/10.1556/2006.2020.00034

Bőthe, B., Tóth-Király, I., Demetrovics, Z., & Orosz, G. (2017). The pervasive role of sex mindset: Beliefs about the malleability of sexual life is linked to higher levels of relationship satisfaction and sexual satisfaction and lower levels of problematic pornography use. *Personality and Individual Differences*, *117*, 15–22. https://doi.org/10.1016/j.paid.2017.05.030

Bőthe, B., Tóth-Király, I., Demetrovics, Z., & Orosz, G. (2020). The short version of the problematic pornography consumption scale (PPCS-6): A reliable and valid measure in general and treatment-seeking populations. *Journal of Sex Research*. https://doi.org/10.1080/00224499.2020.1716205

Bőthe, B., Tóth-Király, I., Potenza, M. N., Griffiths, M. D., Orosz, G., & Demetrovics, Z. (2019). Revisiting the Role of Impulsivity and Compulsivity in Problematic Sexual Behaviors. *The Journal of Sex Research*, *56*(2), 166–179. https://doi.org/10.1080/00224499.2018.1480744

Bőthe, B., Tóth-Király, I., Potenza, M. N., Orosz, G., & Demetrovics, Z. (2020). High-Frequency Pornography Use May Not Always Be Problematic. *The Journal of Sexual Medicine*, *17*(4), 793–811. https://doi.org/10.1016/J.JSXM.2020.01.007

Bőthe, B., Tóth-Király, I., Zsila, Á., Griffiths, M. D., Demetrovics, Z., & Orosz, G. (2017). The Development of the Problematic Pornography Consumption Scale (PPCS). *Https://Doi.Org/10.1080/00224499.2017.1291798*, *55*(3), 395–406. https://doi.org/10.1080/00224499.2017.1291798

Bőthe, B., Vaillancourt-Morel, M.-P., Bergeron, S., Hermann, Z., Ivaskevics, K., Kraus, S. W., Grubbs, J. B., & PPUMLSC (Griffiths, M. D. ). (2024). Uncovering the most robust predictors of problematic pornography use: A large-scale machine learning study across 16 countries. *Journal of Psychopathology and Clinical Science*. https://doi.org/10.1037/abn0000913

Bőthe, B., Vaillancourt-Morel, M.-P., Dion, J., Paquette, M.-M., Massé-Pfister, M., Tóth-Király, I., & Bergeron, S. (2022). A Longitudinal Study of Adolescents' Pornography Use Frequency, Motivations, and Problematic Use Before and During the COVID-19 Pandemic. *Archives of Sexual Behavior*, *51*(1), 139–156. https://doi.org/10.1007/s10508-021-02282-4

Brand, M., Antons, S., Wegmann, E., & Potenza, M. N. (2019). Theoretical Assumptions on Pornography Problems Due to Moral Incongruence and Mechanisms of Addictive or Compulsive Use of Pornography: Are the Two "Conditions" as Theoretically Distinct as Suggested? *Archives of Sexual Behavior*, *48*(2), 417–423. https://doi.org/10.1007/s10508-018-1293-5

Brand, M., Rumpf, H.-Jü., Demetrovics, Z., MÜller, A., Stark, R., King, D. L., Goudriaan, A. E., Mann, K., Trotzke, P., Fineberg, N. A., Chamberlain, S. R., Kraus, S. W., Wegmann, E., Billieux, J., & Potenza, M. N. (2020). Which conditions should be considered as disorders in the International Classification of Diseases (ICD-11) designation of 'other specified disorders due to addictive behaviors'? *Journal of Behavioral Addictions*, *11*(2), 150–159. https://doi.org/10.1556/2006.2020.00035

Brand, M., Snagowski, J., Laier, C., & Maderwald, S. (2016). Ventral striatum activity when watching preferred pornographic pictures is correlated with symptoms of Internet pornography addiction. *NeuroImage*, *129*, 224–232. https://doi.org/10.1016/j.neuroimage.2016.01.033

Brand, M., Young, K. S., Laier, C., Wölfling, K., & Potenza, M. N. (2016). Integrating psychological and neurobiological considerations regarding the development and maintenance of specific Internet-use disorders: An Interaction of Person-Affect-Cognition-Execution (I-PACE) model. *Neuroscience & Biobehavioral Reviews*, *71*, 252–266. https://doi.org/10.1016/j.neubiorev.2016.08.033

Brannigan, R., Cronin, F., McEvoy, O., Stanistreet, D., & Layte, R. (2023). Verification of the Goldilocks Hypothesis: The association between screen use, digital media and psychiatric symptoms in the Growing Up in Ireland study. *Social Psychiatry and Psychiatric Epidemiology*, *58*(8), 1259–1264. https://doi.org/10.1007/s00127-022-02352-5

Bresin, K., Hatfield, O., Ahrenholtz, M. S., & Verona, E. (2024). The Role of Positive and Negative Affect in Illicit Substance Use and Alcohol Use: An Ecological Momentary Assessment Study. *Journal of Studies on Alcohol and Drugs*, jsad.23-00067. https://doi.org/10.15288/jsad.23-00067

Bridges, A. J., & Morokoff, P. J. (2011). Sexual media use and relational satisfaction in heterosexual couples. *Personal Relationships*, *18*(4), 562–585.

Briken, P. (2020). An integrated model to assess and treat compulsive sexual behaviour disorder. *Nature Reviews Urology*, *17*(7), 391–406. https://doi.org/10.1038/s41585-020-0343-7

Brody, S., & Krüger, T. H. C. (2006). The post-orgasmic prolactin increase following intercourse is greater than following masturbation and suggests greater satiety. *Biological Psychology*, *71*(3), 312–315. https://doi.org/10.1016/j.biopsycho.2005.06.008

Brooks, S., & Califf, C. (2017). Social media-induced technostress: Its impact on the job performance of it professionals and the moderating role of job characteristics. *Computer Networks, 114*, 143–153. https://doi.org/10.1016/j.comnet.2016.08.020

Bryazka, D., Reitsma, M. B., Griswold, M. G., Abate, K. H., Abbafati, C., Abbasi-Kangevari, M., Abbasi-Kangevari, Z., Abdoli, A., Abdollahi, M., Abdullah, A. Y. M., Abhilash, E. S., Abu-Gharbieh, E., Acuna, J. M., Addolorato, G., Adebayo, O. M., Adekanmbi, V., Adhikari, K., Adhikari, S., Adnani, Q. E. S., … Gakidou, E. (2022). Population-level risks of alcohol consumption by amount, geography, age, sex, and year: A systematic analysis for the Global Burden of Disease Study 2020. *The Lancet*, *400*(10347), 185–235. https://doi.org/10.1016/S0140-6736(22)00847-9

Bunta, A. (2021). In Times of ‘Chastity’: An Inquiry into Some Recent Developments in the Field of Perversion. *Filozofski Vestnik*, *42*(1).

Burke, L. E., Shiffman, S. M., Music, E., Styn, M. A., Kriska, A., Smailagic, A., Siewiorek, D., Ewing, L. J., Chasens, E., French, B., Mancino, J., Mendez, D., Strollo, P., & Rathbun, S. L. (2017). Ecological Momentary Assessment in Behavioral Research: Addressing Technological and Human Participant Challenges. *Journal of Medical Internet Research*, *19*(3), e77. https://doi.org/10.2196/jmir.7138

Bürkner, P.-C. (2017). brms: An R Package for Bayesian Multilevel Models Using Stan. *Journal of Statistical Software*, *80*, 1–28. https://doi.org/10.18637/jss.v080.i01

Burnett, S. (2022). The Battle for “NoFap”: Myths, Masculinity, and the Meaning of Masturbation Abstention. *Men and Masculinities*, *25*(3), 477–496. https://doi.org/10.1177/1097184X211018256

Burri, A., & Carvalheira, A. (2019). Masturbatory Behavior in a Population Sample of German Women. *The Journal of Sexual Medicine*, *16*(7), 963–974. https://doi.org/10.1016/j.jsxm.2019.04.015

Butler, M. H., Pereyra, S. A., Draper, T. W., Leonhardt, N. D., & Skinner, K. B. (2018). Pornography Use and Loneliness: A Bidirectional Recursive Model and Pilot Investigation. *Journal of Sex & Marital Therapy*, *44*(2), 127–137. https://doi.org/10.1080/0092623X.2017.1321601

Cahill, C. M., Walwyn, W., Taylor, A. M. W., Pradhan, A. A. A., & Evans, C. J. (2016). Allostatic Mechanisms of Opioid Tolerance Beyond Desensitization and Downregulation. *Trends* *in Pharmacological Sciences*, *37*(11), 963–976. https://doi.org/10.1016/j.tips.2016.08.002

Calabrese, E. J. (2008a). Addiction and Dose Response: The Psychomotor Stimulant Theory of Addiction Reveals That Hormetic Dose Responses Are Dominant. *Critical Reviews in Toxicology*, *38*(7), 599–617. https://doi.org/10.1080/10408440802026315

Calabrese, E. J. (2008b). Hormesis and medicine. *British Journal of Clinical Pharmacology*, *66*(5), 594–617. https://doi.org/10.1111/j.1365-2125.2008.03243.x

Calabrese, E. J. (2008c). Stress Biology and Hormesis: The Yerkes–Dodson Law in Psychology—A Special Case of the Hormesis Dose Response. *Critical Reviews in Toxicology*, *38*(5), 453–462. https://doi.org/10.1080/10408440802004007

Calabrese, E. J., & Blain, R. (2005). The occurrence of hormetic dose responses in the toxicological literature, the hormesis database: An overview. *Toxicology and Applied Pharmacology*, *202*(3), 289–301. https://doi.org/10.1016/j.taap.2004.06.023

Calabrese, E. J., & Blain, R. B. (2009). Hormesis and plant biology. *Environmental Pollution*, *157*(1), 42–48. https://doi.org/10.1016/j.envpol.2008.07.028

Calabrese, E. J., & Rubio-Casillas, A. (2018). Biphasic effects of THC in memory and cognition. *European Journal of Clinical Investigation*, *48*(5), e12920. https://doi.org/10.1111/eci.12920

Camacho, M., Moura, A. R., & Oliveira-Maia, A. J. (2018). Compulsive Sexual Behaviors Treated With Naltrexone Monotherapy. *The Primary Care Companion for CNS Disorders*, *20*(1), 26143. https://doi.org/10.4088/PCC.17l02109

Cameron, C. (2012). *Electronic Porn in the Workplace: A Policy Examination* (SSRN Scholarly Paper No. 2254554). https://papers.ssrn.com/abstract=2254554

Candia, C., Jara-Figueroa, C., Rodriguez-Sickert, C., Barabási, A.-L., & Hidalgo, C. A. (2019). The universal decay of collective memory and attention. *Nature Human Behaviour*, *3*(1), Article 1. https://doi.org/10.1038/s41562-018-0474-5

Cannon, W. B. (1929). Organization for physiological homeostasis. *Physiological Reviews*, *9*(3), 399–431. https://doi.org/10.1152/physrev.1929.9.3.399

Cardoso, J., Ramos, C., Brito, J., & Almeida, T. C. (2023). Difficulties in Emotion Regulation and Problematic Pornography Use: The Mediating Role of Loneliness. *International Journal of Sexual Health*, *0*(0), 1–13. https://doi.org/10.1080/19317611.2023.2224807

Carroll, J. S., Padilla-Walker, L. M., Nelson, L. J., Olson, C. D., McNamara Barry, C., & Madsen, S. D. (2008). Generation XXX: Pornography Acceptance and Use Among Emerging Adults. *Journal of Adolescent Research*, *23*(1), 6–30. https://doi.org/10.1177/0743558407306348

Carvalho, J., Štulhofer, A., Vieira, A. L., & Jurin, T. (2015). Hypersexuality and high sexual desire: Exploring the structure of problematic sexuality. *The Journal of Sexual Medicine*, *12*(6), 1356–1367. https://doi.org/10.1111/jsm.12865

Chasioti, D., & Binnie, J. (2021). Exploring the Etiological Pathways of Problematic Pornography Use in NoFap/PornFree Rebooting Communities: A Critical Narrative Analysis of

Internet Forum Data. *Archives of Sexual Behavior*, *50*(5), 2227–2243. https://doi.org/10.1007/S10508-021-01930-Z/FIGURES/1

Chelliah, J. (2014). Policing pornography in the workplace: The case of Australia Post. *Human Resource Management International Digest*, *22*(2), 39–41. https://doi.org/10.1108/HRMID-03-2014-0031

Chen, L., Jiang, X., Luo, X., Kraus, S. W., & Bőthe, B. (2022). The role of impaired control in screening problematic pornography use: Evidence from cross-sectional and longitudinal studies in a large help-seeking male sample. *Psychology of Addictive Behaviors*, *36*(5), 537–546. https://doi.org/10.1037/adb0000714

Chen, L., Jiang, X., Wang, Q., Bőthe, B., Potenza, Marc. N., & Wu, H. (2022). The Association between the Quantity and Severity of Pornography Use: A Meta-analysis. *The Journal of Sex Research*, *59*(6), 704–719. https://doi.org/10.1080/00224499.2021.1988500

Chen, L., Wang, D., Wang, H., Zhang, Y., & Jiang, X. (2023). Moderating Role of Sexual Attitudes in the Association between Online Sexual Activity and Problematic Pornography Use: Evidence from the Chinese Community and Help-Seeking Men. *International Journal of Sexual Health*, *0*(0), 1–18. https://doi.org/10.1080/19317611.2023.2257688

Chen, L., Zaharia, M., & Zou, J. (2023). *How is ChatGPT's behavior changing over time?* (No. arXiv:2307.09009). arXiv. https://doi.org/10.48550/arXiv.2307.09009

Cheng, V. W. S., Davenport, T., Johnson, D., Vella, K., & Hickie, I. B. (2019). Gamification in Apps and Technologies for Improving Mental Health and Well-Being: Systematic Review. *JMIR Ment Health 2019;6(6):E13717 Https://Mental.Jmir.Org/2019/6/E13717*, *6*(6), e13717. https://doi.org/10.2196/13717

Childs, E., Lutz, J. A., & de Wit, H. (2017). Dose-related effects of delta-9-THC on emotional responses to acute psychosocial stress. *Drug and Alcohol Dependence*, *177*, 136–144. https://doi.org/10.1016/j.drugalcdep.2017.03.030

Chou, T., & D'Orsogna, M. R. (2022). A mathematical model of reward-mediated learning in drug addiction. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, *32*(2), 021102. https://doi.org/10.1063/5.0082997

Chu, H.-Y., Gu, Q., Jin, G.-Z., Hu, G.-Y., & Zhen, X. (2010). Electrophysiological Effects of SKF83959 on Hippocampal CA1 Pyramidal Neurons: Potential Mechanisms for the Drug's Neuroprotective Effects. *PLoS ONE*, *5*(10), e13118. https://doi.org/10.1371/journal.pone.0013118

Cinelli, M., De Francisci Morales, G., Galeazzi, A., Quattrociocchi, W., & Starnini, M. (2021). The echo chamber effect on social media. *Proceedings of the National Academy of Sciences*, *118*(9), e2023301118. https://doi.org/10.1073/pnas.2023301118

Colbert, S., Thornton, L., & Richmond, R. (2020). Smartphone apps for managing alcohol consumption: A literature review. *Addiction Science \& Clinical Practice*, *15*, 1–16.

Coletto, M., Aiello, L. M., Lucchese, C., & Silvestri, F. (2017). Adult content consumption in online social networks. *Social Network Analysis and Mining*, *7*(1), 28. https://doi.org/10.1007/s13278-017-0449-y

Colombo, M., & Concone, D. (2019). PS-08-009 Post-Coitial dysphoria: A knowledge survey in the Italian male population. *The Journal of Sexual Medicine*, *16*(5), S28–S29. https://doi.org/10.1016/j.jsxm.2019.03.113

Comulada, W. S., Swendeman, D., & Wu, N. (2016). Cell phone-based ecological momentary assessment of substance use context for Latino youth in outpatient treatment: Who, what, when and where. *Drug and Alcohol Dependence*, *167*, 207–213.

Constantine, L. L. and M. (1981). *Children and Sex: New Findings, New Perspectives*. Eweb:35314. https://repository.library.georgetown.edu/handle/10822/788772

Cooper, A. (1998). Sexuality and the Internet: Surfing into the new millennium. *CyberPsychology \& Behavior*, *1*(2), 187–193.

Cooper, A., Putnam, D. E., Planchon, L. A., & Boies, S. C. (1999). Online sexual compulsivity: Getting tangled in the net. *Sexual Addiction \& Compulsivity: The Journal of Treatment and Prevention*, *6*(2), 79–104.

Crabbe, M., Flood, M., & Adams, K. (2024). Pornography exposure and access among young Australians: A cross-sectional study. *Australian and New Zealand Journal of Public Health*, *48*(3), 100135. https://doi.org/10.1016/j.anzjph.2024.100135

Crosby, J. M., & Twohig, M. P. (2016). Acceptance and Commitment Therapy for Problematic Internet Pornography Use: A Randomized Trial. *Behavior Therapy*, *47*(3), 355–366. https://doi.org/10.1016/j.beth.2016.02.001

Crosby, J. M., Twohig, M. P., Bates, S. C., Higbee, T. S., Domenech Rodríguez, M., & Burnham, B. R. (2011). *Acceptance and Commitment Therapy for the Treatment of Compulsive Pornography Use: A Randomized Clinical Trial*.

Csajka, C., & Verotta, D. (2006). Pharmacokinetic–Pharmacodynamic Modelling: History and Perspectives. *Journal of Pharmacokinetics and Pharmacodynamics*, *33*(3), 227–279. https://doi.org/10.1007/s10928-005-9002-0

Csako, R. I., Rowland, D. L., Hevesi, K., Vitalis, E., & Balalla, S. (2022). Female Sexuality in Aotearoa/New Zealand: Factors and Sexual Response Associated with Masturbation. *International Journal of Sexual Health*, *34*(4), 521–539. https://doi.org/10.1080/19317611.2022.2099499

Csete, M. E., & Doyle, J. C. (2002). Reverse Engineering of Biological Complexity. *Science*, *295*(5560), 1664–1669. https://doi.org/10.1126/science.1069981

Csikszentmihalyi, M., & Figurski, T. J. (1982). Self-awareness and aversive experience in everyday life. *Journal of Personality*, *50*(1), 15–19. https://doi.org/10.1111/j.1467-6494.1982.tb00742.x

Cui, Z., Mo, M., Chen, Q., Wang, X., Yang, H., Zhou, N., Sun, L., Liu, J., Ao, L., & Cao, J. (2021). Pornography Use Could Lead to Addiction and Was Associated With Reproductive Hormone Levels and Semen Quality: A Report From the MARHCS Study in China. *Frontiers in Endocrinology*, *12*. https://doi.org/10.3389/FENDO.2021.736384

Currin, C. B., Vera, S. V., & Khaledi-Nasab, A. (2022). Depolarization of echo chambers by random dynamical nudge. *Scientific Reports*, *12*(1), Article 1. https://doi.org/10.1038/s41598-022-12494-w

Curry, S., Marlatt, G. A., & Gordon, J. R. (1987). Abstinence violation effect: Validation of an attributional construct with smoking cessation. *Journal of Consulting and Clinical Psychology*, *55*(2), 145–149. https://doi.org/10.1037/0022-006X.55.2.145

Daneback, K., Traeen, B., & Månsson, S.-A. (2009). Use of pornography in a random sample of Norwegian heterosexual couples. *Archives of Sexual Behavior*, *38*(5), 746–753. https://doi.org/10.1007/s10508-008-9314-4

Davidson, J. K., & Darling, C. A. (1993). Masturbatory guilt and sexual responsiveness among post-college-age women: Sexual satisfaction revisited. *Journal of Sex & Marital Therapy*, *19*(4), 289–300. https://doi.org/10.1080/00926239308404372

Davidson, R. J. (1998). Affective Style and Affective Disorders: Perspectives from Affective Neuroscience. *Cognition and Emotion*, *12*(3), 307–330. https://doi.org/10.1080/026999398379628

Dawson, K., Tafro, A., & Štulhofer, A. (2019). Adolescent sexual aggressiveness and pornography use: A longitudinal assessment. *Aggressive Behavior*, *45*(6), 587–597. https://doi.org/10.1002/ab.21854

de Vries, L. P., Baselmans, B. M. L., & Bartels, M. (2021). Smartphone-Based Ecological Momentary Assessment of Well-Being: A Systematic Review and Recommendations for Future Studies. *Journal of Happiness Studies*, *22*(5), 2361–2408. https://doi.org/10.1007/s10902-020-00324-7

Dejonckheere, E., Mestdagh, M., Kuppens, P., & Tuerlinckx, F. (2020). Reply to: Context matters for affective chronometry. *Nature Human Behaviour*, *4*(7), 690–693. https://doi.org/10.1038/s41562-020-0861-6

Deng, C., Zhao, Q., & Shukla, R. (2000). Detecting hormesis using a non-parametric rank test. *Human & Experimental Toxicology*, *19*(12), 703–708. https://doi.org/10.1191/096032700676918637

Dhaoui, A., & Bacha, S. (2017). Investor emotional biases and trading volume's asymmetric response: A non-linear ARDL approach tested in S&P500 stock market. *Cogent Economics & Finance*, *5*(1), 1274225. https://doi.org/10.1080/23322039.2016.1274225

Disabato, D. J., Goodman, F. R., Kashdan, T. B., Short, J. L., & Jarden, A. (2016). Different types of well-being? A cross-cultural examination of hedonic and eudaimonic well-being. *Psychological Assessment*, *28*(5), 471–482. https://doi.org/10.1037/pas0000209

Dover, C. R., Leonhardt, N. D., & Edwards, M. H. (2024). Labels Are For Soup Cans: How Self-Labeling as "Addicted" to Pornography Is Associated with Negative Outcomes. *Archives of Sexual Behavior*. https://doi.org/10.1007/s10508-024-02966-7

Dumas, E. O., & Pollack, G. M. (2008). Opioid Tolerance Development: A Pharmacokinetic/Pharmacodynamic Perspective. *The AAPS Journal*, *10*(4), 537–551. https://doi.org/10.1208/s12248-008-9056-1

Durkheim, E. (1893). The Division of Labor in Society. In *Social Theory Re-Wired* (2nd ed.). Routledge.

Eisenberg, R. S. (2007). Look at biological systems through an engineer's eyes. *Nature*, *447*(7143), Article 7143. https://doi.org/10.1038/447376a

Elhai, J. D., Dvorak, R. D., Levine, J. C., & Hall, B. J. (2017). Problematic smartphone use: A conceptual overview and systematic review of relations with anxiety and depression psychopathology. *Journal of Affective Disorders*, *207*, 251–259. https://doi.org/10.1016/j.jad.2016.08.030

Elmokadem, A., Riggs, M. M., & Baron, K. T. (2019). Quantitative Systems Pharmacology and Physiologically-Based Pharmacokinetic Modeling With mrgsolve: A Hands-On Tutorial. *CPT: Pharmacometrics & Systems Pharmacology*, *8*(12), 883–893. https://doi.org/10.1002/psp4.12467

Epstein, D. H., & Preston, K. L. (2012). TGI Monday?: Drug-Dependent Outpatients Report Lower Stress and More Happiness at Work than Elsewhere. *The American Journal on Addictions*, *21*(3), 189–198. https://doi.org/10.1111/j.1521-0391.2012.00230.x

Etchells, P. J., Gage, S. H., Rutherford, A. D., & Munafò, M. R. (2016). Prospective Investigation of Video Game Use in Children and Subsequent Conduct Disorder and Depression Using Data from the Avon Longitudinal Study of Parents and Children. *PLOS ONE*, *11*(1), e0147732. https://doi.org/10.1371/journal.pone.0147732

Etz, A., & Vandekerckhove, J. (2016). A Bayesian Perspective on the Reproducibility Project: Psychology. *PLOS ONE*, *11*(2), e0149794. https://doi.org/10.1371/journal.pone.0149794

Everett, A. C., Graul, B. E., Ronström, J. W., Robinson, J. K., Watts, D. B., España, R. A., Siciliano, C. A., & Yorgason, J. T. (2022). Effectiveness and Relationship between Biased and Unbiased Measures of Dopamine Release and Clearance. *ACS Chemical Neuroscience*. https://doi.org/10.1021/acschemneuro.2c00033

Fagan, P. F. (2009). The effects of pornography on individuals, marriage, family, and community. *Marriage and Religion Research Institute*, 1–26.

Fahs, B., & Frank, E. (2014). Notes from the Back Room: Gender, Power, and (In)Visibility in Women's Experiences of Masturbation. *The Journal of Sex Research*, *51*(3), 241–252. https://doi.org/10.1080/00224499.2012.745474

Feidakis, M. (2011). Emotional scaffolding with respect to time factors in Networking Collaborative Learning Environments. *eLearn Center Research Paper Series*, *0*, 26–36.

Fernandez, D. P., Kuss, D., & Griffiths, M. (2020). Short-term abstinence effects across potential behavioral addictions: A systematic review. *Clinical Psychology Review*, *76*, 101828. https://doi.org/10.1016/j.cpr.2020.101828

Fernandez, D. P., Kuss, D. J., & Griffiths, M. D. (2021a). Lived Experiences of Recovery from Compulsive Sexual Behavior among Members of Sex and Love Addicts Anonymous: A Qualitative Thematic Analysis. *Sexual Health & Compulsivity*, *28*(1–2), 47–80. https://doi.org/10.1080/26929953.2021.1997842

Fernandez, D. P., Kuss, D. J., & Griffiths, M. D. (2021b). The Pornography "Rebooting" Experience: A Qualitative Analysis of Abstinence Journals on an Online Pornography Abstinence Forum. *Archives of Sexual Behavior*, *50*(2), 711–728. https://doi.org/10.1007/s10508-020-01858-w

Fernandez, D. P., Kuss, D. J., Justice, L. V., Fernandez, E. F., & Griffiths, M. D. (2023). Effects of a 7-Day Pornography Abstinence Period on Withdrawal-Related Symptoms in Regular Pornography Users: A Randomized Controlled Study. *Archives of Sexual Behavior*. https://doi.org/10.1007/s10508-022-02519-w

Fiallos, A. M., Bricault, S. J., Cai, L. X., Worku, H. A., Colonnese, M. T., Westmeyer, G. G., & Jasanoff, A. (2017). Reward magnitude tracking by neural populations in ventral striatum. *NeuroImage*, *146*, 1003–1015. https://doi.org/10.1016/j.neuroimage.2016.10.036

Fisher, W. A., Montgomery-Graham, S., & Kohut, T. (2019). Pornography Problems Due to Moral Incongruence. *Archives of Sexual Behavior*, *48*(2), 425–429. https://doi.org/10.1007/s10508-018-1291-7

Floyd, C. G., & Grubbs, J. B. (2022). Context Matters: How Religion and Morality Shape Pornography Use Effects. *Current Sexual Health Reports*. https://doi.org/10.1007/s11930-022-00329-8

Friedman, A., Frankel, M., Flaumenhaft, Y., Merenlender, A., Pinhasov, A., Feder, Y., Taler, M., Gil-Ad, I., Abeles, M., & Yadid, G. (2009). Programmed Acute Electrical Stimulation of Ventral Tegmental Area Alleviates Depressive-Like Behavior. *Neuropsychopharmacology*, *34*(4), Article 4. https://doi.org/10.1038/npp.2008.177

Galarreta, M., & Hestrin, S. (1998). Frequency-dependent synaptic depression and the balance of excitation and inhibition in the neocortex. *Nature Neuroscience*, *1*(7), 587–594. https://doi.org/10.1038/2822

Gårdmark, M., Brynne, L., Hammarlund-Udenaes, M., & Karlsson, M. O. (1999). Interchangeability and Predictive Performance of Empirical Tolerance Models. *Clinical Pharmacokinetics*, *36*(2), 145–167. https://doi.org/10.2165/00003088-199936020-00005

Gardner, E. L. (2011). Addiction and Brain Reward and Antireward Pathways. *Advances in Psychosomatic Medicine*, *30*, 22–60. https://doi.org/10.1159/000324065

Ge, Y., Zhao, S., Zhou, H., Pei, C., Sun, F., Ou, W., & Zhang, Y. (2020). Understanding Echo Chambers in E-commerce Recommender Systems. *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*, 2261–2270. https://doi.org/10.1145/3397271.3401431

George, O., Le Moal, M., & Koob, G. F. (2012). Allostasis and addiction: Role of the dopamine and corticotropin-releasing factor systems. *Physiology & Behavior*, *106*(1), 58–64. https://doi.org/10.1016/j.physbeh.2011.11.004

Gesztelyi, R., Zsuga, J., Kemeny-Beke, A., Varga, B., Juhasz, B., & Tosaki, A. (2012). The Hill equation and the origin of quantitative pharmacology. *Archive for History of Exact Sciences*, *66*(4), 427–438. https://doi.org/10.1007/s00407-012-0098-5

Gilbert, D. G., Rabinovich, N. E., Gilbert-Matuskowitz, E. A., Klein, K. P., & Pergadia, M. L. (2019). Smoking abstinence symptoms across 67 days compared with randomized controls—Moderation by nicotine replacement therapy, bupropion, and negative-affect traits. *Experimental and Clinical Psychopharmacology*, *27*(6), 536–551. https://doi.org/10.1037/pha0000278

Giorgi, V., Bongiovanni, S., Atzeni, F., Marotto, D., Salaffi, F., & Sarzi-Puttini, P. (2020). Adding medical cannabis to standard analgesic treatment for fibromyalgia: A prospective observational study. *Clinical and Experimental Rheumatology*, 53–59.

Gola, M., Wordecha, M., Marchewka, A., & Sescousse, G. (2016). Visual Sexual Stimuli—Cue or Reward? A Perspective for Interpreting Brain Imaging Findings on Human Sexual

Behaviors. *Frontiers in Human Neuroscience*, *10*, 402. https://doi.org/10.3389/fnhum.2016.00402

Gola, M., Wordecha, M., Sescousse, G., Lew-Starowicz, M., Kossowski, B., Wypych, M., Makeig, S., Potenza, M. N., & Marchewka, A. (2017). Can Pornography be Addictive? An fMRI Study of Men Seeking Treatment for Problematic Pornography Use. *Neuropsychopharmacology*, *42*(10), Article 10. https://doi.org/10.1038/npp.2017.78

Gold, S. N., & Heffner, C. L. (1998). Sexual addiction: Many conceptions, minimal data. *Clinical Psychology Review*, *18*(3), 367–381. https://doi.org/10.1016/s0272-7358(97)00051-2

Goldschmidt, A. B., Wonderlich, S. A., Crosby, R. D., Engel, S. G., Lavender, J. M., Peterson, C. B., Crow, S. J., Cao, L., & Mitchell, J. E. (2014). Ecological momentary assessment of stressful events and negative affect in bulimia nervosa. *Journal of Consulting and Clinical Psychology*, *82*(1), 30–39. https://doi.org/10.1037/a0034974

Goldstein, I., & Komisaruk, B. R. (2018). Pathophysiology and Medical Management of Female Orgasmic Illness Syndrome. In *Textbook of Female Sexual Function and Dysfunction* (pp. 239–243). John Wiley & Sons, Ltd. https://doi.org/10.1002/9781119266136.ch17

Gottman, J. M., Coan, J., Carrere, S., & Swanson, C. (1998). Predicting Marital Happiness and Stability from Newlywed Interactions. *Journal of Marriage and Family*, *60*(1), 5–22. https://doi.org/10.2307/353438

Goutelle, S., Maurin, M., Rougier, F., Barbaut, X., Bourguignon, L., Ducher, M., & Maire, P. (2008). The Hill equation: A review of its capabilities in pharmacological modelling. *Fundamental & Clinical Pharmacology*, *22*(6), 633–648. https://doi.org/10.1111/j.1472-8206.2008.00633.x

Grandjean, P. (2016). Paracelsus Revisited: The Dose Concept in a Complex World. *Basic & Clinical Pharmacology & Toxicology*, *119*(2), 126–132. https://doi.org/10.1111/bcpt.12622

Granger, C. W. J. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: Journal of the Econometric Society*, 424–438.

Granjon, D., Leemput, V. van, Perrier, V., & Rudolf, I. (2024). *shinyMobile: Mobile Ready 'shiny' Apps with Standalone Capabilities*. https://github.com/RinteRface/shinyMobile

Grant, J. E., Brewer, J. A., & Potenza, M. N. (2006). The Neurobiology of Substance and Behavioral Addictions. *CNS Spectrums*, *11*(12), 924–930. https://doi.org/10.1017/S109285290001511X

Grant Weinandy, J. T., Lee, B., Hoagland, K. C., Grubbs, J. B., & Bőthe, B. (2023). Anxiety and Compulsive Sexual Behavior Disorder: A Systematic Review. *The Journal of Sex Research*, *60*(4), 545–557. https://doi.org/10.1080/00224499.2022.2066616

Griffiths, M. (2005). A 'components' model of addiction within a biopsychosocial framework. *Journal of Substance Use*, *10*(4), 191–197. https://doi.org/10.1080/14659890500114359

Griffiths, M. D. (2012). Internet sex addiction: A review of empirical research. *Addiction Research & Theory*, *20*(2), 111–124. https://doi.org/10.3109/16066359.2011.588351

Groat, S., Tront, J., & Marchany, R. (2012). Advancing the defense in depth model. *2012 7th International Conference on System of Systems Engineering (SoSE)*, 285–290.

Groves, P. M., & Thompson, R. F. (1970). Habituation: A dual-process theory. *Psychological Review*, *77*(5), 419–450. https://doi.org/10.1037/h0029810

Grubbs, J. B., Exline, J. J., Pargament, K. I., Hook, J. N., & Carlisle, R. D. (2015). Transgression as Addiction: Religiosity and Moral Disapproval as Predictors of Perceived Addiction to Pornography. *Archives of Sexual Behavior*, *44*(1), 125–136. https://doi.org/10.1007/s10508-013-0257-z

Grubbs, J. B., Exline, J. J., Pargament, K. I., Volk, F., & Lindberg, M. J. (2017). Internet Pornography Use, Perceived Addiction, and Religious/Spiritual Struggles. *Archives of Sexual Behavior*, *46*(6), 1733–1745. https://doi.org/10.1007/s10508-016-0772-9

Grubbs, J. B., Floyd, C. G., Griffin, K. R., Jennings, T. L., & Kraus, S. W. (2022). Moral incongruence and addiction: A registered report. *Psychology of Addictive Behaviors*, *36*, 749–761. https://doi.org/10.1037/adb0000876

Grubbs, J. B., Grant, J. T., Lee, B. N., Hoagland, K. C., Davidson, P., Reid, R. C., & Kraus, S. W. (2020). Sexual addiction 25 years on: A systematic and methodological review of empirical literature and an agenda for future research. *Clinical Psychology Review*, 101925.

Grubbs, J. B., & Hook, J. N. (2016). Religion, Spirituality, and Sexual Addiction: A Critical Evaluation of Converging Fields. *Https://Doi.Org/10.1080/10720162.2016.1150925*, *23*(2–3), 155–166. https://doi.org/10.1080/10720162.2016.1150925

Grubbs, J. B., & Kraus, S. W. (2021). Pornography Use and Psychological Science: A Call for Consideration. *Current Directions in Psychological Science*, *30*(1), 68–75. https://doi.org/10.1177/0963721420979594

Grubbs, J. B., Kraus, S. W., & Perry, S. L. (2019). Self-reported addiction to pornography in a nationally representative sample: The roles of use habits, religiousness, and moral incongruence. *Journal of Behavioral Addictions*, *8*(1), 88–93. https://doi.org/10.1556/2006.7.2018.134

Grubbs, J. B., Lee, B. N., Hoagland, K. C., Kraus, S. W., & Perry, S. L. (2020). Addiction or Transgression? Moral Incongruence and Self-Reported Problematic Pornography Use in a Nationally Representative Sample. *Clinical Psychological Science*, *8*(5), 936–946. https://doi.org/10.1177/2167702620922966

Grubbs, J. B., & Perry, S. L. (2019). Moral Incongruence and Pornography Use: A Critical Review and Integration. *The Journal of Sex Research*, *56*(1), 29–37. https://doi.org/10.1080/00224499.2018.1427204

Grubbs, J. B., Perry, S. L., Grant Weinandy, J. T., & Kraus, S. W. (2022). Porndemic? A Longitudinal Study of Pornography Use Before and During the COVID-19 Pandemic in a Nationally Representative Sample of Americans. *Archives of Sexual Behavior*, *51*(1), 123–137. https://doi.org/10.1007/s10508-021-02077-7

Grubbs, J. B., Perry, S. L., Wilt, J. A., & Reid, R. C. (2019a). Pornography problems due to moral incongruence: An integrative model with a systematic review and meta-analysis. *Archives of Sexual Behavior*, *48*(2), 397–415.

Grubbs, J. B., Perry, S., Wilt, J. A., & Reid, R. C. (2019b). Response to Commentaries. *Archives of Sexual Behavior*, *48*(2), 461–468. https://doi.org/10.1007/s10508-019-1406-9

Grubbs, J. B., Sessoms, J., Wheeler, D. M., & Volk, F. (2010). The Cyber-Pornography Use Inventory: The Development of a New Assessment Instrument. *Sexual Addiction & Compulsivity*, *17*(2), 106–126. https://doi.org/10.1080/10720161003776166

Grubbs, J. B., Stauner, N., Exline, J. J., Pargament, K. I., & Lindberg, M. J. (2015). Perceived addiction to Internet pornography and psychological distress: Examining relationships concurrently and over time. *Psychology of Addictive Behaviors*, *29*(4), 1056.

Grubbs, J. B., Volk, F., Exline, J. J., & Pargament, K. I. (2015). Internet pornography use: Perceived addiction, psychological distress, and the validation of a brief measure. *Journal of Sex & Marital Therapy*, *41*(1), 83–106. https://doi.org/10.1080/0092623X.2013.842192

Guidry, R., Floyd, C. G., Volk, F., & Moen, C. E. (2020). The exacerbating impact of moral disapproval on the relationship between pornography use and depression, anxiety, and relationship satisfaction. *Journal of Sex \& Marital Therapy*, *46*(2), 103–121.

Gustafson, D. H., McTavish, F. M., Chih, M. Y., Atwood, A. K., Johnson, R. A., Boyle, M. G., Levy, M. S., Driscoll, H., Chisholm, S. M., Dillenburg, L., Isham, A., & Shah, D. (2014). A Smartphone Application to Support Recovery From Alcoholism: A Randomized Clinical Trial. *JAMA Psychiatry*, *71*(5), 566–572. https://doi.org/10.1001/JAMAPSYCHIATRY.2013.4642

Haghighat, R. (2007). The Development of the Brief Social Desirability Scale (BSDS). *Europe's Journal of Psychology*, *3*(4), Article 4. https://doi.org/10.5964/ejop.v3i4.417

Hald, G. M. (2006). Gender Differences in Pornography Consumption among Young Heterosexual Danish Adults. *Archives of Sexual Behavior*, *35*(5), 577–585. https://doi.org/10.1007/s10508-006-9064-0

Hall, M., Scherner, P. V., Kreidel, Y., & Rubel, J. A. (2021). A Systematic Review of Momentary Assessment Designs for Mood and Anxiety Symptoms. *Frontiers in Psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.642044

Hamaker, E. L., Kuiper, R. M., & Grasman, R. P. P. P. (2015). A critique of the cross-lagged panel model. *Psychological Methods*, *20*(1), 102–116. https://doi.org/10.1037/a0038889

Hanseder, S., & Dantas, J. A. R. (2023). Males' Lived Experience with Self-Perceived Pornography Addiction: A Qualitative Study of Problematic Porn Use. *International Journal of Environmental Research and Public Health*, *20*(2), Article 2. https://doi.org/10.3390/ijerph20021497

Harari, G. M., Müller, S. R., Mishra, V., Wang, R., Campbell, A. T., Rentfrow, P. J., & Gosling, S. D. (2017). An Evaluation of Students' Interest in and Compliance With Self-Tracking Methods: Recommendations for Incentives Based on Three Smartphone Sensing Studies. *Social Psychological and Personality Science*, *8*(5), 479–492. https://doi.org/10.1177/1948550617712033

Harper, C., & Hodgins, D. C. (2016). Examining Correlates of Problematic Internet Pornography Use Among University Students. *Journal of Behavioral Addictions*, *5*(2), 179–191. https://doi.org/10.1556/2006.5.2016.022

Haug, S., Paz Castro, R., Wenger, A., & Schaub, M. P. (2018). Efficacy of a mobile phone-based life-skills training program for substance use prevention among adolescents: Study protocol of a cluster-randomised controlled trial. *BMC Public Health*, *18*(1), 1102. https://doi.org/10.1186/S12889-018-5969-5/TABLES/1

Hayes, S. C., Luoma, J. B., Bond, F. W., Masuda, A., & Lillis, J. (2006). Acceptance and Commitment Therapy: Model, processes and outcomes. *Behaviour Research and Therapy*, *44*(1), 1–25. https://doi.org/10.1016/j.brat.2005.06.006

Hays, R. D., & DiMatteo, M. R. (1987). A Short-Form Measure of Loneliness. *Journal of Personality Assessment*, *51*(1), 69–81. https://doi.org/10.1207/s15327752jpa5101_6

Heller, A. S., Fox, A. S., Wing, E. K., McQuisition, K. M., Vack, N. J., & Davidson, R. J. (2015). The Neurodynamics of Affect in the Laboratory Predicts Persistence of Real-World Emotional Responses. *Journal of Neuroscience*, *35*(29), 10503–10509. https://doi.org/10.1523/JNEUROSCI.0569-15.2015

Henderson, A. A., Matthews, R. A., & Ford, M. T. (2023). The temporal dynamics between work stressors and health behaviors. *Journal of Occupational Health Psychology*, *28*(1), 1–19. https://doi.org/10.1037/ocp0000341

Hendrick, S. S., Dicke, A., & Hendrick, C. (1998). The Relationship Assessment Scale. *Journal of Social and Personal Relationships*, *15*(1), 137–142. https://doi.org/10.1177/0265407598151009

Heninger, S. T. (2016). A Pilot Trial of the Effectiveness of Acceptance and Commitment Therapy Self-Help for Problematic Pornography Viewing. *Undergraduate Honors Capstone Projects*. https://doi.org/10.26076/472d-e4a6

Henrich, J., Heine, S. J., & Norenzayan, A. (2010). The weirdest people in the world? *Behavioral and Brain Sciences*, *33*(2–3), 61–83.

Henry, J. A., Galvez, G., Turbin, M. B., Thielman, E. J., McMillan, G. P., & Istvan, J. A. (2012). Pilot study to evaluate ecological momentary assessment of tinnitus. *Ear and Hearing*, *32*(2), 179.

Henry, N. (2023). *Behavioral Posology: A Novel Paradigm for Modeling the Healthy Limits of Behaviors*. https://doi.org/10.17605/OSF.IO/SAU4V

Henry, N. (2024a). *Appendices for PhD Thesis—The Opponent Process Model of Problematic Pornography Use: Building a Foundation for Adaptive Digital Interventions*. https://doi.org/10.17605/OSF.IO/CK597

Henry, N. (2024b). *CRUD-Capable Mobile Apps with R and shinyMobile: A Case Study in Rapid Prototyping* (No. arXiv:2409.00582). arXiv. https://doi.org/10.48550/arXiv.2409.00582

Henry, N., Donkin, L., Williams, M., & Pedersen, M. (2022). mHealth Technologies for Managing Problematic Pornography Use: Content Analysis. *JMIR Formative Research*, *6*(10), e39869. https://doi.org/10.2196/39869

Henry, N. I. N., Pedersen, M., Williams, M., Martin, J. L. B., & Donkin, L. (2025). Reducing echo chamber effects: An allostatic regulator for recommendation algorithms. *Journal of Psychology and AI*, *1*(1), 2517191. https://doi.org/10.1080/29974100.2025.2517191

Henry, N., Pedersen, M., Williams, M., & Donkin, L. (2023). Behavioral Posology: A Novel Paradigm for Modeling the Healthy Limits of Behaviors. *Advanced Theory and Simulations*, 2300214. https://doi.org/10.1002/adts.202300214

Henry, N., Pedersen, M., Williams, M., Martin, J. L. B., & Donkin, L. (2024). *A Hormetic Approach to the Value-Loading Problem: Preventing the Paperclip Apocalypse?* (No. arXiv:2402.07462). arXiv. https://doi.org/10.48550/arXiv.2402.07462

Herman, J. (2013). Neural Control of Chronic Stress Adaptation. *Frontiers in Behavioral Neuroscience*, *7*, 61. https://doi.org/10.3389/fnbeh.2013.00061

Heron, K. E., & Smyth, J. M. (2010). Ecological momentary interventions: Incorporating mobile technology into psychosocial and health behaviour treatments. *British Journal of Health Psychology*, *15*(1), 1–39.

Hevesi, K., Tamas, S., & Rowland, D. L. (2023). Why Men Masturbate: Reasons and Correlates in Men with and without Sexual Dysfunction. *Journal of Sex & Marital Therapy*, *49*(7), 783–797. https://doi.org/10.1080/0092623X.2023.2204088

Hilton, D. L., & Watts, C. (2011). Pornography addiction: A neuroscience perspective. *Surgical Neurology International*, *2*, 19. https://doi.org/10.4103/2152-7806.76977

Hilton Jr, D. L. (2013). Pornography addiction—A supranormal stimulus considered in the context of neuroplasticity. *Socioaffective Neuroscience \& Psychology*, *3*(1), 20767.

Ho, R. C., Zhang, M. W., Tsang, T. Y., Toh, A. H., Pan, F., Lu, Y., Cheng, C., Yip, P. S., Lam, L. T., Lai, C.-M., Watanabe, H., & Mak, K.-K. (2014). The association between internet addiction and psychiatric co-morbidity: A meta-analysis. *BMC Psychiatry*, *14*(1), 183. https://doi.org/10.1186/1471-244X-14-183

Hoagland, K. C., Rotruck, H. L., Moore, J. N., & Grubbs, J. B. (2023). Reasons for Moral-Based Opposition to Pornography in a U.S. Nationally Representative Sample. *Journal of Sex & Marital Therapy*, 1–22. https://doi.org/10.1080/0092623X.2023.2186992

Hodges, E. L., Marshall, J. P., & Ashpole, N. M. (2020). Age-dependent hormesis-like effects of the synthetic cannabinoid CP55940 in C57BL/6 mice. *Npj Aging and Mechanisms of Disease*, *6*(1), Article 1. https://doi.org/10.1038/s41514-020-0045-7

Hodgins, D. C., el-Guebaly, N., & Armstrong, S. (1995). Prospective and retrospective reports of mood states before relapse to substance use. *Journal of Consulting and Clinical Psychology*, *63*(3), 400–407. https://doi.org/10.1037/0022-006X.63.3.400

Hoza, B., Pelham, W. E., Sams, S. E., & Carlson, C. (1992). An Examination of the ‘Dosage’ Effects of Both Behavior Therapy and Methylphenidate on the Classroom Performance of Two ADHD Children. *Behavior Modification*, *16*(2), 164–192. https://doi.org/10.1177/01454455920162002

Huang, S., Borgland, S. L., & Zamponi, G. W. (2019). Peripheral nerve injury-induced alterations in VTA neuron firing properties. *Molecular Brain*, *12*(1), 89. https://doi.org/10.1186/s13041-019-0511-y

Huckins, J. F., DaSilva, A. W., Hedlund, E. L., Murphy, E. I., Rogers, C., Wang, W., Obuchi, M., Holtzheimer, P. E., Wagner, D. D., & Campbell, A. T. (2020). Causal factors of anxiety and depression in college students: Longitudinal ecological momentary assessment and causal analysis using Peter and Clark momentary conditional independence. *JMIR Mental Health*, *7*(6), e16684.

Hurlbert, D. F., & Whittaker, K. E. (1991). The Role of Masturbation in Marital and Sexual Satisfaction: A Comparative Study of Female Masturbators and Nonmasturbators.

*Journal of Sex Education and Therapy*, *17*(4), 272–282. https://doi.org/10.1080/01614576.1991.11074029

Huțul, T.-D., & Karner-Huțuleac, A. (2024). The Roles of Frequency of Pornography Use, and Moral Incongruence in the Relationship Between Sexual Satisfaction, and Psychological Distress Related to the Use of Pornography: A Moderated Mediation Model. *International Journal of Sexual Health*, *0*(0), 1–14. https://doi.org/10.1080/19317611.2024.2349592

Ibarra, M., Vázquez, M., & Fagiolino, P. (2020). Current PBPK Models: Are They Predicting Tissue Drug Concentration Correctly? *Drugs in R&D*, *20*(4), 295–299. https://doi.org/10.1007/s40268-020-00325-0

Igboanugo, S., & Mielke, J. G. (2023). The allostatic load model: A framework to understand the cumulative multi-system impact of work-related psychosocial stress exposure among firefighters. *Health Psychology and Behavioral Medicine*, *11*(1), 2255026. https://doi.org/10.1080/21642850.2023.2255026

Ince, C., Albertella, L., Liu, C., Tiego, J., Fontenelle, L. F., Chamberlain, S. R., Yücel, M., & Rotaru, K. (2024). Problematic pornography use and novel patterns of escalating use: A cross-sectional network analysis with two independent samples. *Addictive Behaviors*, *156*, 108048. https://doi.org/10.1016/j.addbeh.2024.108048

Ince, C., Fontenelle, L. F., Carter, A., Albertella, L., Tiego, J., Chamberlain, S. R., & Rotaru, K. (2023). Clarifying and extending our understanding of problematic pornography use through descriptions of the lived experience. *Scientific Reports*, *13*(1), 18193. https://doi.org/10.1038/s41598-023-45459-8

Ince, C., Yücel, M., Albertella, L., & Fontenelle, L. F. (2021). Exploring the clinical profile of problematic pornography use. *CNS Spectrums*, *26*(6), 648–657. https://doi.org/10.1017/S1092852920001686

Interian, R., Marzo, R. G., Mendoza, I., & Ribeiro, C. C. (2023). Network polarization, filter bubbles, and echo chambers: An annotated review of measures and reduction methods. *International Transactions in Operational Research*, *30*(6), 3122–3158. https://doi.org/10.1111/itor.13224

Irving, G., & Askell, A. (2019). AI Safety Needs Social Scientists. *Distill*, *4*(2), e14. https://doi.org/10.23915/distill.00014

Jarosz, A. F., Colflesh, G. J. H., & Wiley, J. (2012). Uncorking the muse: Alcohol intoxication facilitates creative problem solving. *Consciousness and Cognition*, *21*(1), 487–493. https://doi.org/10.1016/j.concog.2012.01.002

Jenkins, M. F. (2018). *An Ethnographic Content Analysis of Postings to an Online Group Forum: Individuals Abstaining from Pornography* [Ph.D., Auburn University]. https://www.proquest.com/docview/2779138040/abstract/BB572C0CC63B4B79PQ/1

Kafka, M. P. (2010). Hypersexual disorder: A proposed diagnosis for DSM-V. *Archives of Sexual Behavior*, *39*(2), 377–400. https://doi.org/10.1007/s10508-009-9574-7

Kafka, M. P. (2014). What Happened to Hypersexual Disorder? *Archives of Sexual Behavior*, *43*(7), 1259–1261. https://doi.org/10.1007/s10508-014-0326-y

Kahana, M. J., & Adler, M. (2017). *Note on the power law of forgetting* [Preprint]. Neuroscience. https://doi.org/10.1101/173765

Kahneman, D., & Tversky, A. (2018). Prospect theory: An analysis of decision under risk. *Experiments in Environmental Economics*, *1*, 143–172. https://doi.org/10.2307/1914185

Katsumi, Y., Theriault, J. E., Quigley, K. S., & Barrett, L. F. (2022). Allostasis as a core feature of hierarchical gradients in the human brain. *Network Neuroscience*, *6*(4), 1010–1031. https://doi.org/10.1162/netn_a_00240

Kaypak, A. C., & Raz, A. (2022). Macrodosing to microdosing with psychedelics: Clinical, social, and cultural perspectives. *Transcultural Psychiatry*, 13634615221119386. https://doi.org/10.1177/13634615221119386

Keles, B., McCrae, N., & Grealish, A. (2020). A systematic review: The influence of social media on depression, anxiety and psychological distress in adolescents. *International Journal of Adolescence and Youth*, *25*(1), 79–93. https://doi.org/10.1080/02673843.2019.1590851

Kim, S. B., Bartell, S. M., & Gillen, D. L. (2016). Inference for the existence of hormetic dose–response relationships in toxicology studies. *Biostatistics (Oxford, England)*, *17*(3), 523–536. https://doi.org/10.1093/biostatistics/kxw004

Kılıç, D., Armstrong, H. L., & Graham, C. A. (2023). The Role of Mutual Masturbation within Relationships: Associations with Sexual Satisfaction and Sexual Self-Esteem. *International Journal of Sexual Health*, *0*(0), 1–20. https://doi.org/10.1080/19317611.2023.2237950

Klein, V., Briken, P., Schröder, J., & Fuss, J. (2019). Mental health professionals' pathologization of compulsive sexual behavior: Does clients' gender and sexual orientation matter? *Journal of Abnormal Psychology*, *128*(5), 465–472. https://doi.org/10.1037/abn0000437

Kober, H., Mende-Siedlecki, P., Kross, E. F., Weber, J., Mischel, W., Hart, C. L., & Ochsner, K. N. (2010). Prefrontal–striatal pathway underlies cognitive regulation of craving. *Proceedings of the National Academy of Sciences*, *107*(33), 14811–14816. https://doi.org/10.1073/pnas.1007779107

Kockler, T. D., Santangelo, P. S., & Ebner-Priemer, U. W. (2018). Investigating Binge Eating Using Ecological Momentary Assessment: The Importance of an Appropriate Sampling Frequency. *Nutrients*, *10*(1), Article 1. https://doi.org/10.3390/nu10010105

Koenig, J., Klier, J., Parzer, P., Santangelo, P., Resch, F., Ebner-Priemer, U., & Kaess, M. (2021). High-frequency ecological momentary assessment of emotional and interpersonal states preceding and following self-injury in female adolescents. *European Child & Adolescent Psychiatry*, *30*(8), 1299–1308. https://doi.org/10.1007/s00787-020-01626-0

Kohut, T., Fisher, W. A., & Campbell, L. (2017). Perceived effects of pornography on the couple relationship: Initial findings of open-ended, participant-informed,'bottom-up' research. *Archives of Sexual Behavior*, *46*(2), 585–602.

Kohut, T., & Štulhofer, A. (2018). The Role of Religiosity in Adolescents' Compulsive Pornography Use: A Longitudinal Assessment. *Journal of Sex & Marital Therapy*, *44*(8), 759–775. https://doi.org/10.1080/0092623X.2018.1466012

Komiya, N., Good, G. E., & Sherrod, N. B. (2000). Emotional openness as a predictor of college students' attitudes toward seeking psychological help. *Journal of Counseling Psychology*, *47*(1), 138–143. https://doi.org/10.1037/0022-0167.47.1.138

Koob, G. F., & Le Moal, M. (1997). Drug abuse: Hedonic homeostatic dysregulation. *Science*, *278*(5335), 52–58.

Koob, G. F., & Le Moal, M. (2001). Drug addiction, dysregulation of reward, and allostasis. *Neuropsychopharmacology*, *24*(2), 97–129.

Koob, G. F., & Moal, M. L. (2008). Neurobiological mechanisms for opponent motivational processes in addiction. *Philosophical Transactions of the Royal Society B: Biological Sciences*. https://doi.org/10.1098/rstb.2008.0094

Koob, G. F., & Volkow, N. D. (2016). Neurobiology of addiction: A neurocircuitry analysis. *The Lancet. Psychiatry*, *3*(8), 760–773. https://doi.org/10.1016/S2215-0366(16)00104-8

Kor, A., Fogel, Y. A., Reid, R. C., & Potenza, M. N. (2013). Should Hypersexual Disorder be Classified as an Addiction? *Sexual Addiction & Compulsivity*, *20*(1–2), 27–47. https://doi.org/10.1080/10720162.2013.768132

Koukounas, E., & Over, R. (2000). Changes in the magnitude of the eyeblink startle response during habituation of sexual arousal. *Behaviour Research and Therapy*, *38*(6), 573–584. https://doi.org/10.1016/s0005-7967(99)00075-3

Kraus, S. W., Krueger, R. B., Briken, P., First, M. B., Stein, D. J., Kaplan, M. S., Voon, V., Abdo, C. H. N., Grant, J. E., Atalla, E., & Reed, G. M. (2018). Compulsive sexual behaviour disorder in the ICD-11. *World Psychiatry*, *17*(1), 109–110. https://doi.org/10.1002/wps.20499

Kraus, S. W., Martino, S., & Potenza, M. N. (2016). Clinical Characteristics of Men Interested in Seeking Treatment for Use of Pornography. *Journal of Behavioral Addictions*, *5*(2), 169–178. https://doi.org/10.1556/2006.5.2016.036

Kraus, S. W., Potenza, M. N., Martino, S., & Grant, J. E. (2015). Examining the psychometric properties of the Yale–Brown Obsessive–Compulsive Scale in a sample of compulsive pornography users. *Comprehensive Psychiatry*, *59*, 117–122. https://doi.org/10.1016/j.comppsych.2015.02.007

Kraus, S. W., & Sweeney, P. J. (2019). Hitting the Target: Considerations for Differential Diagnosis When Treating Individuals for Problematic Use of Pornography. *Archives of Sexual Behavior*, *48*(2), 431–435. https://doi.org/10.1007/s10508-018-1301-9

Krieke, L. van der, Emerencia, A. C., Bos, E. H., Rosmalen, J. G., Riese, H., Aiello, M., Sytema, S., & Jonge, P. de. (2015). Ecological Momentary Assessments and Automated Time Series Analysis to Promote Tailored Health Care: A Proof-of-Principle Study. *JMIR Research Protocols*, *4*(3), e4000. https://doi.org/10.2196/resprot.4000

Krueger, R. B. (2016). Diagnosis of hypersexual or compulsive sexual behavior can be made using ICD-10 and DSM-5 despite rejection of this diagnosis by the American Psychiatric Association. *Addiction*, *111*, 2110–2111. https://doi.org/10.1111/add.13366

Krüger, T. H. C., Giraldi, A., & Tenbergen, G. (2021). The Neurobiology of Sexual Responses and Its Clinical Relevance. In M. Lew-Starowicz, A. Giraldi, & T. H. C. Krüger (Eds.), *Psychiatry and Sexual Medicine: A Comprehensive Guide for Clinical Practitioners* (pp. 71–84). Springer International Publishing. https://doi.org/10.1007/978-3-030-52298-8_7

Krüger, T., Haake, P., Chereath, D., Knapp, W., Janssen, O., Exton, M., Schedlowski, M., & Hartmann, U. (2003). Specificity of the neuroendocrine response to orgasm during sexual arousal in men. *Journal of Endocrinology*, *177*(1), 57–64. https://doi.org/10.1677/joe.0.1770057

Krüger, T., Haake, P., Haverkamp, J., Kramer, M., Exton, M., Saller, B., Leygraf, N., Hartmann, U., & Schedlowski, M. (2003). Effects of acute prolactin manipulation on sexual drive and function in males. *Journal of Endocrinology*, *179*(3), 357–365. https://doi.org/10.1677/joe.0.1790357

Kruglanski, A. W. (2017). Motivational phases on the road to action. *Motivation Science, 3*(3), 196.

Kruglanski, A. W., Chernikova, M., Rosenzweig, E., & Kopetz, C. (2014). On motivational readiness. *Psychological Review, 121*(3), 367.

Kruschke, J. K., & Liddell, T. M. (2018). Bayesian data analysis for newcomers. *Psychonomic Bulletin & Review*, *25*(1), 155–177. https://doi.org/10.3758/s13423-017-1272-1

Kuiper, R. M., & Ryan, O. (2018). Drawing Conclusions from Cross-Lagged Relationships: Re-Considering the Role of the Time-Interval. *Structural Equation Modeling: A Multidisciplinary Journal*, *25*(5), 809–823. https://doi.org/10.1080/10705511.2018.1431046

Kuppens, P., Oravecz, Z., & Tuerlinckx, F. (2010). Feelings change: Accounting for individual differences in the temporal dynamics of affect. *Journal of Personality and Social Psychology*, *99*(6), 1042–1060. https://doi.org/10.1037/a0020962

Lafaye, G., Karila, L., Blecha, L., & Benyamina, A. (2017). Cannabis, cannabinoids, and health. *Dialogues in Clinical Neuroscience*, *19*(3), 309–316. https://doi.org/10.31887/DCNS.2017.19.3/glafaye

Lambert, N. M., Negash, S., Stillman, T. F., Olmstead, S. B., & Fincham, F. D. (2012). A love that doesn't last: Pornography consumption and weakened commitment to one's romantic partner. *Journal of Social and Clinical Psychology, 31*(4), 410–438.

Lastella, M., O'Mullan, C., Paterson, J. L., & Reynolds, A. C. (2019). Sex and Sleep: Perceptions of Sex as a Sleep Promoting Behavior in the General Adult Population. *Frontiers in Public Health*, *7*. https://www.frontiersin.org/articles/10.3389/fpubh.2019.00033

Lavian, H., & Korngreen, A. (2019). Short-term depression shapes information transmission in a constitutively active GABAergic synapse. *Scientific Reports*, *9*(1), 18092. https://doi.org/10.1038/s41598-019-54607-y

Lee, R. S. C., Hoppenbrouwers, S., & Franken, I. (2019). A Systematic Meta-Review of Impulsivity and Compulsivity in Addictive Behaviors. *Neuropsychology Review*, *29*(1), 14–26. https://doi.org/10.1007/s11065-019-09402-x

Leonhardt, N. D., & Willoughby, B. J. (2018). Longitudinal Links between Pornography Use, Marital Importance, and Permissive Sexuality During Emerging Adulthood. *Marriage & Family Review*, *54*(1), 64–84. https://doi.org/10.1080/01494929.2017.1359811

Levenson, J. C., Shensa, A., Sidani, J. E., Colditz, J. B., & Primack, B. A. (2016). The association between social media use and sleep disturbance among young adults. *Preventive Medicine*, *85*, 36–41. https://doi.org/10.1016/j.ypmed.2016.01.001

Levy, Y., Levy, D., Barto, A., & Meyer, J. (2013). A Computational Hypothesis for Allostasis: Delineation of Substance Dependence, Conventional Therapies, and Alternative Treatments. *Frontiers in Psychiatry*, *4*. https://www.frontiersin.org/article/10.3389/fpsyt.2013.00167

Lewczuk, K., Glica, A., Nowakowska, I., Gola, M., & Grubbs, J. B. (2020). Evaluating Pornography Problems Due to Moral Incongruence Model. *The Journal of Sexual Medicine*, *17*(2), 300–311. https://doi.org/10.1016/J.JSXM.2019.11.259

Lewczuk, K., Nowakowska, I., Lewandowska, K., Potenza, M. N., & Gola, M. (2021). Frequency of use, moral incongruence and religiosity and their relationships with self-perceived addiction to pornography, internet use, social networking and online gaming. *Addiction*, *116*(4), 889–899. https://doi.org/10.1111/ADD.15272

Lewczuk, K., Szmyd, J., Skorko, M., & Gola, M. (2017). Treatment seeking for problematic pornography use among women. *Journal of Behavioral Addictions*, *6*(4), 445–456. https://doi.org/10.1556/2006.6.2017.063

Lewczuk, K., Wizła, M., Glica, A., Potenza, M. N., Lew-Starowicz, M., & Kraus, S. W. (2022). Withdrawal and tolerance as related to compulsive sexual behavior disorder and problematic pornography use – Preregistered study based on a nationally representative sample in Poland. *Journal of Behavioral Addictions*, *1*(aop). https://doi.org/10.1556/2006.2022.00076

Lewczuk, K., Wójcik, A., & Gola, M. (2022). Increase in the Prevalence of Online Pornography Use: Objective Data Analysis from the Period Between 2004 and 2016 in Poland. *Archives of Sexual Behavior*, *51*(2), 1157–1171. https://doi.org/10.1007/s10508-021-02090-w

Lew-Starowicz, M., & Coleman, E. (2022). Mental and sexual health perspectives of the International Classification of Diseases (ICD-11) Compulsive Sexual Behavior Disorder •. *Journal of Behavioral Addictions*, *11*(2), 226–229. https://doi.org/10.1556/2006.2022.00032

Ley, D., Prause, N., & Finn, P. (2014). The Emperor Has No Clothes: A Review of the 'Pornography Addiction' Model. *Current Sexual Health Reports 2014 6:2*, *6*(2), 94–105. https://doi.org/10.1007/S11930-014-0016-8

Li, X., Yang, T., & Sun, Z. (2019). Hormesis in health and chronic diseases. *Trends in Endocrinology and Metabolism: TEM*, *30*(12), 944–958. https://doi.org/10.1016/j.tem.2019.08.007

Li, Y.-W., Hill, G., Wong, H., Kelly, N., Ward, K., Pierdomenico, M., Ren, S., Gilligan, P., Grossman, S., Trainor, G., Taub, R., McElroy, J., & Zazcek, R. (2003). Receptor Occupancy of Nonpeptide Corticotropin-Releasing Factor 1 Antagonist DMP696: Correlation with Drug Exposure and Anxiolytic Efficacy. *Journal of Pharmacology and Experimental Therapeutics*, *305*(1), 86–96. https://doi.org/10.1124/jpet.102.045914

Lioy, P. J. (2010). Exposure Science: A View of the Past and Milestones for the Future. *Environmental Health Perspectives*, *118*(8), 1081–1090. https://doi.org/10.1289/ehp.0901634

Loban, M., Dräger, J., & Bardid, F. (2024). *Associations between screen time and mental health in childhood and adolescence: Findings from the Millennium Cohort Study*. https://doi.org/10.31219/osf.io/ez56s

Lotfi, A., Babakhanin, M., & Ghazanfarpour, M. (2021). The effectiveness of intervention with cognitive behavioral therapy on pornography: A systematic review protocol of randomized clinical trial studies. *Health Science Reports*, *4*(3), e341.

Love, T., Laier, C., Brand, M., Hatch, L., & Hajela, R. (2015). Neuroscience of Internet Pornography Addiction: A Review and Update. *Behavioral Sciences*, *5*(3), Article 3. https://doi.org/10.3390/bs5030388

Lucumi, Y., Nieva-Posso, D. A., & García-Perdomo, H. A. (2024). Pornography consumption and its effect on sexual performance in young men: Urology point of view. *International Journal of Urological Nursing*, *18*(3), e12420. https://doi.org/10.1111/ijun.12420

Ludwigs, K., Lucas, R., Veenhoven, R., Richter, D., & Arends, L. (2020). Can Happiness Apps Generate Nationally Representative Datasets? - A Case Study Collecting Data on People's Happiness Using the German Socio-Economic Panel. *Applied Research in Quality of Life*, *15*(4), 1135–1149. https://doi.org/10.1007/s11482-019-09723-2

Luhmann, M., & Intelisano, S. (2018). Hedonic Adaptation and the Set Point for Subjective Well-Being. *In E. Diener, S. Oishi, & L. Tay (Eds.), Handbook of Well-Being.*, 27.

Lukasiewicz, M., Fareng, M., Benyamina, A., Blecha, L., Reynaud, M., & Falissard, B. (2007). Ecological momentary assessment in addiction. *Expert Review of Neurotherapeutics*, *7*(8), 939–950.

Lungu, A., & Linehan, M. M. (2017). Chapter 18 - Dialectical Behavior Therapy: Overview, Characteristics, and Future Directions. In S. G. Hofmann & G. J. G. Asmundson (Eds.), *The Science of Cognitive Behavioral Therapy* (pp. 429–459). Academic Press. https://doi.org/10.1016/B978-0-12-803457-6.00018-0

Lyngs, U., Lukoff, K., Csuka, L., Slovák, P., Van Kleek, M., & Shadbolt, N. (2022). The Goldilocks level of support: Using user reviews, ratings, and installation numbers to investigate digital self-control tools. *International Journal of Human-Computer Studies*, *166*, 102869. https://doi.org/10.1016/j.ijhcs.2022.102869

Lyngs, U., Lukoff, K., Slovak, P., Binns, R., Slack, A., Inzlicht, M., Van Kleek, M., & Shadbolt, N. (2019). Self-control in cyberspace: Applying dual systems theory to a review of digital self-control tools. *Conference on Human Factors in Computing Systems - Proceedings*. https://doi.org/10.1145/3290605.3300361

Maddux, J. E. (1995). Self-Efficacy Theory. In J. E. Maddux (Ed.), *Self-Efficacy, Adaptation, and Adjustment: Theory, Research, and Application* (pp. 3–33). Springer US. https://doi.org/10.1007/978-1-4419-6868-5_1

Maitland, D. W. M., & Neilson, E. C. (2023). Associations Between Pornography Consumption Patterns, Pornography Consumption Motives, and Social Wellbeing among U.S. College Students: A Latent Profile Analysis with a Primarily Female Sample. *Journal of Sex & Marital Therapy*, 1–16. https://doi.org/10.1080/0092623X.2023.2193182

Major, S. D., Fisher, A. R., Top Jr, D. N., Gardenhire, B., & Myers, E. (2024). Shaking the Sound Relationship House: Pornography Use and Relationship Functioning of Men Married to

Women. *Journal of Couple & Relationship Therapy*, *0*(0), 1–19. https://doi.org/10.1080/15332691.2024.2367636

Maliňáková, K., Černá, A., Fürstová, J., Čermák, I., Trnka, R., & Tavel, P. (2019). Psychometric analysis of the Guilt and Shame Experience Scale (GSES). *Československá Psychologie: Časopis Pro Psychologickou Teorii a Praxi*, *63*(2), 177–192.

Manning, J. C. (2006). The Impact of Internet Pornography on Marriage and the Family: A Review of the Research. *Sexual Addiction & Compulsivity*, *13*(2–3), 131–165. https://doi.org/10.1080/10720160600870711

Manojlovich, M., & Sidani, S. (2008). Nurse dose: What's in a concept? *Research in Nursing & Health*, *31*(4), 310–319. https://doi.org/10.1002/nur.20265

Marshall, E. A., & Miller, H. A. (2024). Age and Type of First Exposure to Pornography: It Matters for Girls and Boys. *Deviant Behavior*, *45*(3), 377–393. https://doi.org/10.1080/01639625.2023.2248338

Massey, P. V., & Bashir, Z. I. (2007). Long-term depression: Multiple forms and implications for brain function. *Trends in Neurosciences*, *30*(4), 176–184. https://doi.org/10.1016/j.tins.2007.02.005

Masters, W. H., & Johnson, V. E. (1966). *Human sexual response*. Little, Brown.

Mattebo, M., Tydén, T., Häggström-Nordin, E., Nilsson, K. W., & Larsson, M. (2018). Pornography consumption and psychosomatic and depressive symptoms among Swedish adolescents: A longitudinal study. *Upsala Journal of Medical Sciences*, *123*(4), 237–246. https://doi.org/10.1080/03009734.2018.1534907

Maxwell, S. R. J. (2012). Pharmacodynamics for the prescriber. *Medicine*, *40*(7), 351–356. https://doi.org/10.1016/j.mpmed.2012.05.002

McGrath, A. (2017). Dealing with dissonance: A review of cognitive dissonance reduction. *Social and Personality Psychology Compass*, *11*(12), e12362. https://doi.org/10.1111/spc3.12362

McGraw, J. S., Grant Weinandy, J. T., Floyd, C. G., Hoagland, C., Kraus, S. W., & Grubbs, J. B. (2024). Problematic pornography use and suicidal thoughts: Results from cross-sectional and longitudinal analyses. *Psychology of Addictive Behaviors*, No Pagination Specified-No Pagination Specified. https://doi.org/10.1037/adb0000996

Mckee, A. (2007). Positive and Negative Effects of Pornography as Attributed by Consumers. *Australian Journal of Communication*, *34*.

McMahon, S. J. (2018). The linear quadratic model: Usage, interpretation and challenges. *Physics in Medicine & Biology*, *64*(1), 01TR01. https://doi.org/10.1088/1361-6560/aaf26a

McNabney, S. M., Hevesi, K., & Rowland, D. L. (2020). Effects of Pornography Use and Demographic Parameters on Sexual Response during Masturbation and Partnered Sex in Women. *International Journal of Environmental Research and Public Health*, *17*(9), Article 9. https://doi.org/10.3390/ijerph17093130

McRuer, T. (1995). Pilot-Induced Oscillations and Human Dynamic Behavior. *NASA Technical Reports Server*.

McVay, M. A., Bennett, G. G., Steinberg, D., & Voils, C. I. (2019). Dose-Response Research in Digital Health Interventions: Concepts, Considerations, and Challenges. *Health Psychology : Official Journal of the Division of Health Psychology, American Psychological Association*, *38*(12), 1168–1174. https://doi.org/10.1037/hea0000805

Mehl, M. R., Conner, T. S., Bolger, N., Fahrenberg, J., Laurenceau, J.-P., Reis, H. T., Stone, A. A., & Tennen, H. (2012). *Handbook of Research Methods for Studying Daily Life*.

Meibohm, B., & Derendorf, H. (1997). Basic concepts of pharmacokinetic/pharmacodynamic (PK/PD) modelling. *International Journal of Clinical Pharmacology and Therapeutics*, *35*(10), 401–413.

Menon, R., & Neumann, I. D. (2023). Detection, processing and reinforcement of social cues: Regulation by the oxytocin system. *Nature Reviews Neuroscience*, 1–17. https://doi.org/10.1038/s41583-023-00759-w

Mestre-Bach, G., & Potenza, M. N. (2023a). Loneliness, Pornography Use, Problematic Pornography Use, and Compulsive Sexual Behavior. *Current Addiction Reports*. https://doi.org/10.1007/s40429-023-00516-0

Mestre-Bach, G., & Potenza, M. N. (2023b). Pornography Use, Problematic Pornography Use, and Potential Impacts on Partners and Relationships. *Current Addiction Reports*. https://doi.org/10.1007/s40429-023-00468-5

Mestre-Bach, G., Villena-Moya, A., & Chiclana-Actis, C. (2023). Pornography Use and Violence: A Systematic Review of the Last 20 Years. *Trauma, Violence, & Abuse*, 15248380231173619. https://doi.org/10.1177/15248380231173619

Miceli, M., & Castelfranchi, C. (2018). Reconsidering the Differences Between Shame and Guilt. *Europe's Journal of Psychology*, *14*(3), 710–733. https://doi.org/10.5964/ejop.v14i3.1564

Michailovs, S., Howard, Z., Pond, S., Fitzgerald, M., Visser, T. A. W., Bell, J., Pinniger, G., Irons, J., Schmitt, M., Stoker, M., Huf, S., & Loft, S. (2024). Sharing imagery and analysis tools in a simulated submarine control room. *Applied Ergonomics*, *114*, 104125. https://doi.org/10.1016/j.apergo.2023.104125

Mick, T. M., & Hollander, E. (2006). Impulsive-compulsive sexual behavior. *CNS Spectrums*, *11*(12), 944–955. https://doi.org/10.1017/s1092852900015133

Mihajlov, M., & Vejmelka, L. (2017). Internet addiction: A review of the first twenty years. *Psychiatria Danubina*, *29*(3), 260–272.

Milas, G., Wright, P., & Štulhofer, A. (2020). Longitudinal Assessment of the Association Between Pornography Use and Sexual Satisfaction in Adolescence. *The Journal of Sex Research*, *57*(1), 16–28. https://doi.org/10.1080/00224499.2019.1607817

Miller, D. J., McBain, K. A., Li, W. W., & Raggatt, P. T. F. (2019). Pornography, preference for porn-like sex, masturbation, and men's sexual and relationship satisfaction. *Personal Relationships*, *26*(1), 93–113. https://doi.org/10.1111/pere.12267

Min, J., Cao, Z., Cui, L., Li, F., Lu, Z., Hou, Y., Yang, H., Wang, X., & Xu, C. (2023). The association between coffee consumption and risk of incident depression and anxiety: Exploring the benefits of moderate intake. *Psychiatry Research*, *326*, 115307. https://doi.org/10.1016/j.psychres.2023.115307

Minarcik, J. (2016). *Proposed Treatment of Problematic Pornography Use: A Cognitive-Behavioral Approach*. University of Arkansas.

Mitchell, A., Wei, P., & Lim, W. A. (2015). Oscillatory stress stimulation uncovers an Achilles' heel of the yeast MAPK signaling network. *Science*, *350*(6266), 1379–1383. https://doi.org/10.1126/science.aab0892

Mithaug, D. E. (1993). *Self-regulation theory: How optimal adjustment maximizes gain* (pp. xv, 233). Praeger Publishers/Greenwood Publishing Group.

Mohr, D. C., Burns, M. N., Schueller, S. M., Clarke, G., & Klinkman, M. (2013). Behavioral intervention technologies: Evidence review and recommendations for future research in mental health. *General Hospital Psychiatry*, *35*(4), 332–338. https://doi.org/10.1016/j.genhosppsych.2013.03.008

Momin, A., Cadiou, H., Mason, A., & McNaughton, P. A. (2008). Role of the hyperpolarization-activated current Ih in somatosensory neurons. *The Journal of Physiology*, *586*(Pt 24), 5911–5929. https://doi.org/10.1113/jphysiol.2008.163154

Morey, R. D., & Rouder, J. N. (2012). *BayesFactor: Computation of Bayes Factors for Common Designs* (p. 0.9.12-4.7) [Dataset]. https://doi.org/10.32614/CRAN.package.BayesFactor

Morichetta, A., Trevisan, M., Vassio, L., & Krickl, J. (2021). Understanding web pornography usage from traffic analysis. *Computer Networks*, *189*, 107909. https://doi.org/10.1016/j.comnet.2021.107909

Morrison, I. (2016). Keep Calm and Cuddle on: Social Touch as a Stress Buffer. *Adaptive Human Behavior and Physiology*, *2*(4), 344–362. https://doi.org/10.1007/s40750-016-0052-x

Mould, D., & Upton, R. (2012). Basic Concepts in Population Modeling, Simulation, and Model-Based Drug Development. *CPT: Pharmacometrics & Systems Pharmacology*, *1*(9), 6. https://doi.org/10.1038/psp.2012.4

Mould, D., & Upton, R. (2013). Basic Concepts in Population Modeling, Simulation, and Model-Based Drug Development—Part 2: Introduction to Pharmacokinetic Modeling Methods. *CPT: Pharmacometrics & Systems Pharmacology*, *2*(4), 38. https://doi.org/10.1038/psp.2013.14

Muntean, I., & Wright, C. D. (2007). Autonomous agency, AI, and allostasis: A biomimetic perspective. *Pragmatics & Cognition*, *15*(3), 485–513. https://doi.org/10.1075/pc.15.3.07mun

Murre, J. M. J., & Dros, J. (2015). Replication and Analysis of Ebbinghaus' Forgetting Curve. *PLoS ONE*, *10*(7), e0120644. https://doi.org/10.1371/journal.pone.0120644

Muusses, L. D., Kerkhof, P., & Finkenauer, C. (2015). Internet pornography and relationship quality: A longitudinal study of within and between partner effects of adjustment, sexual satisfaction and sexually explicit internet material among newly-weds. *Computers in Human Behavior*, *45*, 77–84. https://doi.org/10.1016/j.chb.2014.11.077

Nahum-Shani, I., Smith, S. N., Spring, B. J., Collins, L. M., Witkiewitz, K., Tewari, A., & Murphy, S. A. (2018). Just-in-Time Adaptive Interventions (JITAIs) in Mobile Health: Key Components and Design Principles for Ongoing Health Behavior Support. *Annals of Behavioral Medicine: A Publication of the Society of Behavioral Medicine*, *52*(6), 446. https://doi.org/10.1007/S12160-016-9830-8

Negus, S. S., Selley, D. E., & Sim-Selley, L. J. (2010). Pharmacodynamic tolerance. *Encyclopedia of Psychopharmacology. Springer-Verlag*, 994–997.

Nelson, L. J., Padilla-Walker, L. M., & Carroll, J. S. (2010). "I believe it is wrong but I still do it": A comparison of religious young men who do versus do not use pornography. *Psychology of Religion and Spirituality*, *2*(3), 136–147. https://doi.org/10.1037/a0019127

Neubauer, A. B., Lerche, V., & Voss, A. (2018). Interindividual differences in the intraindividual association of competence and well-being: Combining experimental and intensive longitudinal designs. *Journal of Personality*, *86*(4), 698–713. https://doi.org/10.1111/jopy.12351

Neuman, S. B. (1988). The Displacement Effect: Assessing the Relation between Television Viewing and Reading Performance. *Reading Research Quarterly*, *23*(4), 414–440. https://doi.org/10.2307/747641

Newlin, D. B., Regalia, P. A., Seidman, T. I., & Bobashev, G. (2012). Control Theory and Addictive Behavior. In B. Gutkin & S. H. Ahmed (Eds.), *Computational Neuroscience of Drug Addiction* (pp. 57–108). Springer. https://doi.org/10.1007/978-1-4614-0751-5_3

Newton, J. D. A., Demant, D., Phillips, J. G., Struckman-Johnson, C., & Oviedo-Trespalacios, O. (2022). Sexual behaviours among dyadic vehicle occupants. *Transportation Research Part F: Traffic Psychology and Behaviour*, *85*, 119–132. https://doi.org/10.1016/j.trf.2021.11.020

*NoFap® Porn Addiction Recovery*. (2022). NoFap. https://nofap.com/

Nolin, M.-C., Daspe, M.-È., Bőthe, B., Brassard, A., Joyal, C., & Vaillancourt-Morel, M.-P. (2024). Associations Between Contents of Pornography and Sexual Satisfaction and Function Among Young Adults. *Journal of Sex Research*, 1–14. https://doi.org/10.1080/00224499.2024.2311874

O'Brien, S. T., Dozo, N., Hinton, J. D. X., Moeck, E. K., Susanto, R., Jayaputera, G. T., Sinnott, R. O., Vu, D., Alvarez-Jimenez, M., Gleeson, J., & Koval, P. (2024). SEMA3: A free smartphone platform for daily life surveys. *Behavior Research Methods*. https://doi.org/10.3758/s13428-024-02445-w

Okabe, Y., Takahashi, F., & Ito, D. (2021). Problematic Pornography Use in Japan: A Preliminary Study Among University Students. *Frontiers in Psychology*, *12*. https://www.frontiersin.org/articles/10.3389/fpsyg.2021.638354

Olds, J. (1956). Pleasure Centers in the Brain. *Scientific American*, *195*(4), 105–117.

Olds, J., & Milner, P. (1954). Positive reinforcement produced by electrical stimulation of septal area and other regions of rat brain. *Journal of Comparative and Physiological Psychology*, *47*, 419–427. https://doi.org/10.1037/h0058775

Orchard, T., & Sangaraganesan, D. M. (2022). Exploring the links between slang and sexual and gender-based violence among university students in a Canadian city. *Sex Education*, *0*(0), 1–15. https://doi.org/10.1080/14681811.2022.2108780

Oviedo-Trespalacios, O., & Phillips, J. G. (2021). Sexual activity while driving: A content analysis of media reports. *Transportation Research Part F: Traffic Psychology and Behaviour*, *80*, 141–149. https://doi.org/10.1016/j.trf.2021.03.020

Owens, E. W., Behun, R. J., Manning, J. C., & Reid, R. C. (2012). The impact of Internet pornography on adolescents: A review of the research. *Sexual Addiction \& Compulsivity*, *19*(1–2), 99–122.

Palazzolo, F., & Bettman, C. (2020). Exploring the Lived Experience of Problematic Users of Internet Pornography: A Qualitative Study. *Sexual Addiction & Compulsivity*, *27*(1–2), 45–64. https://doi.org/10.1080/10720162.2020.1766610

Panksepp, J. (1998). *Affective neuroscience: The foundations of human and animal emotions* (pp. xii, 466). Oxford University Press.

Paolillo, E. W., Obermeit, L. C., Tang, B., Depp, C. A., Vaida, F., Moore, D. J., & Moore, R. C. (2018). Smartphone-based ecological momentary assessment (EMA) of alcohol and cannabis use in older adults with and without HIV infection. *Addictive Behaviors*, *83*, 102–108. https://doi.org/10.1016/j.addbeh.2017.10.016

Pareek, S., Jain, G., & Gupta, R. K. (2023). Efficacy of Mindfulness Meditation as a Therapeutic Tool in Problematic Pornography Consumption. *Sexual Health & Compulsivity*, *0*(0), 1–15. https://doi.org/10.1080/26929953.2023.2270620

*Parental control and digital wellbeing software*. (2022). Qustodio. https://www.qustodio.com/en/

Parsons, J. T., Kelly, B. C., Bimbi, D. S., Meunch, F., & Morgenstern, J. (2007). Accounting for the Social Triggers of Sexual Compulsivity. *Journal of Addictive Diseases*. https://doi.org/10.1300/J069v26n03_02

Patel, P. C., Wolfe, M. T., & Williams, T. A. (2019). Self-employment and allostatic load. *Journal of Business Venturing*, *34*(4), 731–751. https://doi.org/10.1016/j.jbusvent.2018.05.004

Patridge, E. F., & Bardyn, T. P. (2018). Research Electronic Data Capture (REDCap). *Journal of the Medical Library Association : JMLA*, *106*(1), 142–144. https://doi.org/10.5195/jmla.2018.319

Paulos, M. R., & Avelliino, G. J. (2020). Post-orgasmic illness syndrome: History and current perspectives. *Fertility and Sterility*, *113*(1), 13–15. https://doi.org/10.1016/j.fertnstert.2019.11.021

Peper, A. (2009). Intermittent Adaptation A Theory of Drug Tolerance, Dependence and Addiction. *Pharmacopsychiatry 2009; 42 (Suppl. 1): S1–S15*, *42*, S1–S15. https://doi.org/10.1055/s-0029-1202848

Peper, A., Grimbergen, C. A., Kraal, J. W., & Engelbart, J. H. (1988). An approach to the modeling of the tolerance mechanism in the drug effect. II: On the implications of compensatory regulation. *Journal of Theoretical Biology*, *132*(1), 29–41. https://doi.org/10.1016/S0022-5193(88)80188-7

Perez, M., Avila, S., Moreira, D., Moraes, D., Testoni, V., Valle, E., Goldenstein, S., & Rocha, A. (2017). Video pornography detection through deep learning techniques and motion information. *Neurocomputing*, *230*, 279–293.

Perrewé, P. L., & McAllister, C. P. (2024). Examining the dynamics of major theories of occupational stress. In *Handbook of occupational health psychology, 3rd ed* (pp. 47–64). American Psychological Association. https://doi.org/10.1037/0000331-003

Perry, S. L. (2016). From bad to worse? Pornography consumption, spousal religiosity, gender, and marital quality. *Sociological Forum*, *31*(2), 441–464.

Perry, S. L. (2017a). Does Viewing Pornography Diminish Religiosity Over Time? Evidence From Two-Wave Panel Data. *Journal of Sex Research*, *54*(2), 214–226. https://doi.org/10.1080/00224499.2016.1146203

Perry, S. L. (2017b). Does Viewing Pornography Reduce Marital Quality Over Time? Evidence from Longitudinal Data. *Archives of Sexual Behavior*, *46*(2), 549–559. https://doi.org/10.1007/s10508-016-0770-y

Perry, S. L. (2018a). Pornography use and depressive symptoms: Examining the role of moral incongruence. *Society and Mental Health*, *8*(3), 195–213.

Perry, S. L. (2018b). Pornography use and marital quality: Testing the moral incongruence hypothesis. *Personal Relationships*, *25*(2), 233–248. https://doi.org/10.1111/pere.12234

Perry, S. L. (2020). Is the Link Between Pornography Use and Relational Happiness Really More About Masturbation? Results From Two National Surveys. *The Journal of Sex Research*, *57*(1), 64–76. https://doi.org/10.1080/00224499.2018.1556772

Perry, S. L., & Davis, J. T. (2017). Are pornography users more likely to experience a romantic breakup? Evidence from longitudinal data. *Sexuality \& Culture*, *21*(4), 1157–1176.

Petersen, J. L., & Hyde, J. S. (2010). A meta-analytic review of research on gender differences in sexuality, 1993-2007. *Psychological Bulletin*, *136*(1), 21–38. https://doi.org/10.1037/a0017504

Peterson, L., & Peterson, M. J. (1959). Short-term retention of individual verbal items. *Journal of Experimental Psychology*, *58*(3), 193–198. https://doi.org/10.1037/h0049234

Picard, R. W. (1997). *Affective computing*. MIT Press.

Pinheiro, J., Bates, D., & R Core Team. (2024). *nlme: Linear and Nonlinear Mixed Effects Models*. https://CRAN.R-project.org/package=nlme

Pinkerton, S. D., Bogart, L. M., Cecil, H., & Abramson, P. R. (2003). Factors Associated with Masturbation in a Collegiate Sample. *Journal of Psychology & Human Sexuality*, *14*(2–3), 103–121. https://doi.org/10.1300/J056v14n02_07

Pistre, N., Schreck, B., Grall-Bronnec, M., & Fatseas, M. (2023). Should problematic sexual behavior be viewed under the scope of addiction? A systematic review based on DSM-5 substance use disorder criteria. *Addictive Behaviors Reports*, 100510. https://doi.org/10.1016/j.abrep.2023.100510

Plaza, I., Demarzo, M. M. P., Herrera-Mercadal, P., & Garc\'\ia-Campayo, J. (2013). Mindfulness-based mobile applications: Literature review and analysis of current features. *JMIR mHealth and uHealth*, *1*(2), e2733.

*Plucky—A self-control filter*. (2022). Plucky. https://www.pluckyfilter.com

Polito, V., & Stevenson, R. J. (2019). A systematic study of microdosing psychedelics. *PLOS ONE*, *14*(2), e0211023. https://doi.org/10.1371/journal.pone.0211023

Porchet, C., Benowitz, L., & Sheiner, B. (1988). *Pharmacodynamic Model of Tolerance: Application to Nicotine*. 6.

Potenza, M. N. (2008). The neurobiology of pathological gambling and drug addiction: An overview and new findings. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *363*(1507), 3181–3189. https://doi.org/10.1098/rstb.2008.0100

Prause, N. (2017). Evaluate Models of High-Frequency Sexual Behaviors Already. *Archives of Sexual Behavior*, *46*(8), 2269–2274. https://doi.org/10.1007/s10508-017-1078-2

Prause, N. (2019). Porn Is for Masturbation. *Archives of Sexual Behavior*, *48*(8), 2271–2277. https://doi.org/10.1007/s10508-019-1397-6

Prause, N., & Binnie, J. (2023). Iatrogenic effects of Reboot/NoFap on public health: A preregistered survey study. *Sexualities*, 13634607231157070. https://doi.org/10.1177/13634607231157070

Prause, N., & Pfaus, J. (2015). Viewing Sexual Stimuli Associated with Greater Sexual Responsiveness, Not Erectile Dysfunction. *Sexual Medicine*, *3*(2), 90–98. https://doi.org/10.1002/sm2.58

Prause, N., Steele, V. R., Staley, C., Sabatinelli, D., & Hajcak, G. (2015). Modulation of late positive potentials by sexual images in problem users and controls inconsistent with 'porn addiction'. *Biological Psychology*, *109*, 192–199. https://doi.org/10.1016/j.biopsycho.2015.06.005

Prekeges, J. L. (2003). Radiation Hormesis, or, Could All That Radiation Be Good for Us? *Journal of Nuclear Medicine Technology*, *31*(1), 11–17.

Price, J., Patterson, R., Regnerus, M., & Walley, J. (2016). How Much More XXX is Generation X Consuming? Evidence of Changing Attitudes and Behaviors Related to Pornography Since 1973. *Journal of Sex Research*, *53*(1), 12–20. https://doi.org/10.1080/00224499.2014.1003773

Przybylski, A. K. (2014). Electronic Gaming and Psychosocial Adjustment. *Pediatrics*, *134*(3), e716–e722. https://doi.org/10.1542/peds.2013-4021

Przybylski, A. K., & Weinstein, N. (2017). A Large-Scale Test of the Goldilocks Hypothesis: Quantifying the Relations Between Digital-Screen Use and the Mental Well-Being of Adolescents. *Psychological Science*, *28*(2), 204–215. https://doi.org/10.1177/0956797616678438

Quilichini, P., & Bernard, C. (2012). Brain state-dependent neuronal computation. *Frontiers in Computational Neuroscience*, *6*, 77. https://doi.org/10.3389/fncom.2012.00077

R Core Team. (2022). *R: A Language and Environment for Statistical Computing*. https://www.R-project.org/

Rajani, N. B., Mastellos, N., & Filippidis, F. T. (2021). Impact of Gamification on the Self-Efficacy and Motivation to Quit of Smokers: Observational Study of Two Gamified Smoking Cessation Mobile Apps. *JMIR Serious Games 2021;9(2):E27290 Https://Games.Jmir.Org/2021/2/E27290*, *9*(2), e27290. https://doi.org/10.2196/27290

Rajman, I. (2008). PK/PD modelling and simulations: Utility in drug development. *Drug Discovery Today*, *13*(7), 341–346. https://doi.org/10.1016/j.drudis.2008.01.003

Raket, L. L. (2020). Statistical Disease Progression Modeling in Alzheimer Disease. *Frontiers in Big Data*, *3*. https://www.frontiersin.org/article/10.3389/fdata.2020.00024

Raket, L. L. (2022). *Disease progression modeling based on nonlinear mixed effects modeling* [R]. https://github.com/larslau/progmod (Original work published 2020)

Ravish, H., Arya, S., & Kumar Sharma, M. (2024). A Narrative Review on Bio-Physiology of Naltrexone Treatment in Pornography Addiction. *ADDICTA: The Turkish Journal on Addictions*, *11*(1), 112–116. https://doi.org/10.5152/ADDICTA.2024.23049

Raylu, N., & Oei, T. P. S. (2002). Pathological gambling: A comprehensive review. *Clinical Psychology Review*, *22*(7), 1009–1061. https://doi.org/10.1016/S0272-7358(02)00101-0

Regan, H. (2021). Playboy and Pornification: 65 Years of the Playboy Centerfold. *Sexuality and Culture*, *25*(3), 1058–1075. https://doi.org/10.1007/S12119-020-09809-2/FIGURES/1

Reid, R. C., Carpenter, B. N., & Hook, J. N. (2016). Investigating Correlates of Hypersexual Behavior in Religious Patients. *Sexual Addiction & Compulsivity*, *23*(2–3), 296–312. https://doi.org/10.1080/10720162.2015.1130002

Reid, R. C., Carpenter, B. N., Hook, J. N., Garos, S., Manning, J. C., Gilliland, R., Cooper, E. B., McKittrick, H., Davtian, M., & Fong, T. (2012). Report of Findings in a DSM-5 Field Trial for Hypersexual Disorder. *The Journal of Sexual Medicine*, *9*(11), 2868–2877. https://doi.org/10.1111/j.1743-6109.2012.02936.x

Reid, R. C., & Kafka, M. P. (2014). Controversies About Hypersexual Disorder and the DSM-5. *Current Sexual Health Reports*, *6*(4), 259–264. https://doi.org/10.1007/s11930-014-0031-9

Reisman, Y., & Tripodi, F. (2022). Post-Orgasmic Illness Syndrome (POIS). In Y. Reisman, L. Lowenstein, & F. Tripodi (Eds.), *Textbook of Rare Sexual Medicine Conditions* (pp. 111–124). Springer International Publishing. https://doi.org/10.1007/978-3-030-98263-8_9

Richards, D., & Richardson, T. (2012). Computer-based psychological treatments for depression: A systematic review and meta-analysis. *Clinical Psychology Review*, *32*(4), 329–342. https://doi.org/10.1016/j.cpr.2012.02.004

Richardson, C. R., Resnick, P. J., Hansen, D. L., Derry, H. A., & Rideout, V. J. (2002). Does pornography-blocking software block access to health information on the Internet? *JAMA*, *288*(22), 2887–2894.

Riediger, M., Schmiedek, F., Wagner, G. G., & Lindenberger, U. (2009). Seeking Pleasure and Seeking Pain: Differences in Prohedonic and Contra-Hedonic Motivation From Adolescence to Old Age. *Psychological Science*, *20*(12), 1529–1535. https://doi.org/10.1111/j.1467-9280.2009.02473.x

Rissel, C., Richters, J., De Visser, R. O., McKee, A., Yeung, A., & Caruana, T. (2017). A profile of pornography users in Australia: Findings from the second Australian study of health and relationships. *The Journal of Sex Research*, *54*(2), 227–240.

Robinson, T. E., & Berridge, K. C. (1993). The neural basis of drug craving: An incentive-sensitization theory of addiction. *Brain Research. Brain Research Reviews*, *18*(3), 247–291. https://doi.org/10.1016/0165-0173(93)90013-p

Robinson, T. E., & Berridge, K. C. (2008). The incentive sensitization theory of addiction: Some current issues. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *363*(1507), 3137–3146. https://doi.org/10.1098/rstb.2008.0093

Rodriguez-Paras, C., Tippey, K., Brown, E., Sasangohar, F., Creech, S., Kum, H.-C., Lawley, M., & Benzer, J. K. (2017). Posttraumatic stress disorder and mobile health: App investigation and scoping literature review. *JMIR mHealth and uHealth*, *5*(10), e156.

Rofarello, A. M., & De Russis, L. (2021). *Coping with Digital Wellbeing in a Multi-Device World; Coping with Digital Wellbeing in a Multi-Device World*. https://doi.org/10.1145/3411764.3445076

Rohrer, J. M., & Murayama, K. (2023). These Are Not the Effects You Are Looking for: Causality and the Within-/Between-Persons Distinction in Longitudinal Data Analysis. *Advances in Methods and Practices in Psychological Science*, *6*(1), 25152459221140842. https://doi.org/10.1177/25152459221140842

Rowland, D. L., & Cooper, S. E. (2017). Treating Men's Orgasmic Difficulties. In *The Wiley Handbook of Sex Therapy* (pp. 72–97). John Wiley & Sons, Ltd. https://doi.org/10.1002/9781118510384.ch6

Rowland, D. L., Donarski, A., Graves, V., Caldwell, C., Hevesi, B., & Hevesi, K. (2019). The Experience of Orgasmic Pleasure during Partnered and Masturbatory Sex in Women with and without Orgasmic Difficulty. *Journal of Sex & Marital Therapy*, *45*(6), 550–561. https://doi.org/10.1080/0092623X.2019.1586021

Rowland, D. L., Hevesi, K., Conway, G. R., & Kolba, T. N. (2020). Relationship Between Masturbation and Partnered Sex in Women: Does the Former Facilitate, Inhibit, or Not Affect the Latter? *The Journal of Sexual Medicine*, *17*(1), 37–47. https://doi.org/10.1016/j.jsxm.2019.10.012

Roza, T. H., Noronha, L. T., Shintani, A. O., Massuda, R., Kessler, F. H. P., & Passos, I. C. (2023). Withdrawal-like Symptoms in Problematic Pornography Use: A Scoping Review. *Journal of Addiction Medicine*, 10.1097/ADM.0000000000001227. https://doi.org/10.1097/ADM.0000000000001227

Rozado, D. (2023). The Political Biases of ChatGPT. *Social Sciences*, *12*(3), Article 3. https://doi.org/10.3390/socsci12030148

*R/pornfree*. (2022). R/Pornfree. https://www.reddit.com/r/pornfree

Ruffing, E. G., Brody, L. R., & Sandage, S. J. (2022). Distress and Satisfaction in Women Who Perceive that Their Male Partners Use Pornography: The Roles of Attitude, Religious Commitment and Conservative Religiosity. *The Journal of Sex Research*, *0*(0), 1–16. https://doi.org/10.1080/00224499.2022.2137097

Saliares, E., Wilkerson, J. M., Sieving, R. E., & Brady, S. S. (2017). Sexually Experienced Adolescents' Thoughts About Sexual Pleasure. *The Journal of Sex Research*, *54*(4–5), 604–618. https://doi.org/10.1080/00224499.2016.1170101

Sangeado, S. (2016). Impact of Pornography Use in Adolescent Boys: Boys' Self-Reports on Their Use of Pornography. *Senior Honors Projects*. https://digitalcommons.uri.edu/srhonorsprog/477

Savva, M. (2022). Real-Time Analytical Solutions as Series Formulas and Heaviside off/on Switch Functions for Multiple Intermittent Intravenous Infusions in One- and Two-Compartment Models. *Journal of Biosciences and Medicines*, *10*(1), Article 1. https://doi.org/10.4236/jbm.2022.101012

Schaub, M. P., Blankers, M., Lehr, D., Boss, L., Riper, H., Dekker, J., Goudriaan, A. E., Maier, L. J., Haug, S., Amann, M., Dey, M., Wenger, A., & Ebert, D. D. (2016). Efficacy of an internet-based self-help intervention to reduce co-occurring alcohol misuse and depression symptoms in adults: Study protocol of a three-arm randomised controlled trial. *BMJ Open*, *6*(5), e011457. https://doi.org/10.1136/BMJOPEN-2016-011457

Schirrmacher, V. (2021). Less Can Be More: The Hormesis Theory of Stress Adaptation in the Global Biosphere and Its Implications. *Biomedicines*, *9*(3), Article 3. https://doi.org/10.3390/biomedicines9030293

Schneggenburger, R., & Forsythe, I. (2006). The calyx of Held. *Cell and Tissue Research*, *326*, 311–337. https://doi.org/10.1007/s00441-006-0272-7

Schofield, E., Hay, J. L., & Li, Y. (2019). Observation Effect in Ecological Momentary Assessments: A Study of Sun Protection Practices. *Journal of Methods and Measurement in the Social Sciences*, *10*(2). https://doi.org/10.2458/v10i2.23786

Schulthess, P., Post, T. M., Yates, J., & van der Graaf, P. H. (2018). Frequency-Domain Response Analysis for Quantitative Systems Pharmacology Models. *CPT: Pharmacometrics & Systems Pharmacology*, *7*(2), 111–123. https://doi.org/10.1002/psp4.12266

Schweitzer, R. D., O’Brien, J., & Burri, A. (2015). Postcoital Dysphoria: Prevalence and Psychological Correlates. *Sexual Medicine*, *3*(4), 235–243. https://doi.org/10.1002/sm2.74

Scott, H., & Woods, H. C. (2019). Understanding Links Between Social Media Use, Sleep and Mental Health: Recent Progress and Current Challenges. *Current Sleep Medicine Reports*, *5*(3), 141–149. https://doi.org/10.1007/s40675-019-00148-9

Sedrati, H., Belrhiti, Z., Nejjari, C., & Ghazal, H. (2022). Evaluation of Mobile Health apps for Non-Medical Cannabis Use: A Scoping Review. *Procedia Computer Science*, *196*, 581–589.

Serre, F., Fatseas, M., Swendsen, J., & Auriacombe, M. (2015). Ecological momentary assessment in the investigation of craving and substance use in daily life: A systematic review. *Drug and Alcohol Dependence*, *148*, 1–20.

Šević, S., Mehulić, J., & Štulhofer, A. (2020). Is pornography a risk for adolescent academic achievement? Findings from two longitudinal studies of male adolescents. *European Journal of Developmental Psychology*, *17*(2), 275–292. https://doi.org/10.1080/17405629.2019.1588104

Sheikh, A. A., Ganai, P. T., Malik, N. A., & Dar, K. A. (2013). Smartphone: Android Vs IOS. *The SIJ Transactions on Computer Science Engineering & Its Applications (CSEA)*, *1*(4), 9.

Shen, N., Levitan, M.-J., Johnson, A., Bender, J. L., Hamilton-Page, M., Jadad, A. A. R., & Wiljer, D. (2015). Finding a depression app: A review and content analysis of the depression app marketplace. *JMIR mHealth and uHealth*, *3*(1), e3713.

Shiffman, S. M., & Stone, A. A. (1998). Ecological momentary assessment: A new tool for behavioral medicine research. In *Technology and methods in behavioral medicine* (pp. 117–131). Lawrence Erlbaum Associates Publishers. https://doi.org/10.4324/9781410602770

Shiffman, S. M., Stone, A. A., & Hufford, M. R. (2008). Ecological Momentary Assessment. *Annual Review of Clinical Psychology*, *4*(1), 1–32. https://doi.org/10.1146/annurev.clinpsy.3.022806.091415

Short, M. B., Wetterneck, C. T., Bistricky, S. L., Shutter, T., & Chase, T. E. (2016). Clinicians' beliefs, observations, and treatment effectiveness regarding clients' sexual addiction and internet pornography use. *Community Mental Health Journal*, *52*(8), 1070–1081.

Silva, B. M. C., Rodrigues, J. J. P. C., de la Torre D\'\iez, I., López-Coronado, M., & Saleem, K. (2015). Mobile-health: A review of current state in 2015. *Journal of Biomedical Informatics*, *56*, 265–272.

Simon, S. C., & Greitemeyer, T. (2019). The impact of immersion on the perception of pornography: A virtual reality study. *Computers in Human Behavior*, *93*, 141–148. https://doi.org/10.1016/J.CHB.2018.12.018

Smets, E. M. A., Garssen, B., Bonke, B., & De Haes, J. C. J. M. (1995). The multidimensional Fatigue Inventory (MFI) psychometric qualities of an instrument to assess fatigue. *Journal of Psychosomatic Research*, *39*(3), 315–325. https://doi.org/10.1016/0022-3999(94)00125-O

Snaith, R. P. (2003). The Hospital Anxiety And Depression Scale. *Health and Quality of Life Outcomes*, *1*(1), 29. https://doi.org/10.1186/1477-7525-1-29

Sniewski, L., Farvid, P., & Carter, P. (2018). The assessment and treatment of adult heterosexual men with self-perceived problematic pornography use: A review. *Addictive Behaviors*, *77*, 217–224. https://doi.org/10.1016/j.addbeh.2017.10.010

Sniewski, L., Krägeloh, C., Farvid, P., & Carter, P. (2022). Meditation as an intervention for men with self-perceived problematic pornography use: A series of single case studies. *Current Psychology*, *41*(8), 5151–5162. https://doi.org/10.1007/s12144-020-01035-1

Solomon, R. L. (1980). The opponent-process theory of acquired motivation: The costs of pleasure and the benefits of pain. *American Psychologist*, *35*, 691–712. https://doi.org/10.1037/0003-066X.35.8.691

Solomon, R. L., & Corbit, J. D. (1974). An opponent-process theory of motivation: I. Temporal dynamics of affect. *Psychological Review*, *81*(2), 119–145. https://doi.org/10.1037/h0036128

Solt, K., Van Dort, C. J., Chemali, J. J., Taylor, N. E., Kenny, J. D., & Brown, E. N. (2014). Electrical Stimulation of the Ventral Tegmental Area Induces Reanimation from General Anesthesia. *Anesthesiology*, *121*(2), 311–319. https://doi.org/10.1097/ALN.0000000000000117

Spek, V., Cuijpers, P., Nyklícek, I., Riper, H., Keyzer, J., & Pop, V. (2007). Internet-based cognitive behaviour therapy for symptoms of depression and anxiety: A meta-analysis. *Psychological Medicine*, *37*(3), 319–328. https://doi.org/10.1017/S0033291706008944

Spinhoven, P., Ormel, J., Sloekers, P. P. A., Kempen, G. I. J. M., Speckens, A. E. M., & Hemert, A. M. V. (1997). A validation study of the Hospital Anxiety and Depression Scale (HADS) in different groups of Dutch subjects. *Psychological Medicine*, *27*(2), 363–370. https://doi.org/10.1017/S0033291796004382

Stack, S., Wasserman, I., & Kern, R. (2004). Adult social bonds and use of internet pornography. *Social Science Quarterly*, *85*(1), 75–88.

Staiger, P. K., O'Donnell, R., Liknaitzky, P., Bush, R., & Milward, J. (2020). Mobile apps to reduce tobacco, alcohol, and illicit drug use: Systematic review of the first decade. *Journal of Medical Internet Research*, *22*(11), e17156.

Starcke, K., Antons, S., Trotzke, P., & Brand, M. (2018). Cue-reactivity in behavioral addictions: A meta-analysis and methodological considerations. *Journal of Behavioral Addictions*, *7*(2), 227–238. https://doi.org/10.1556/2006.7.2018.39

Stark, R., Markert, C., Golder, S., Psarros, R., Discher, J. P., Khatib, S., Metzger, J., Palmer, S., Rechmann, J., Storz, F., Walter, B., Allard, S., Antons, S., Bledzka, M., Brand, M., Dörrenbächer, S., Englisch, J., Friehs, T., Gonçalves, K. D. C., … Heinz, C. (2024). The PornLoS Treatment Program: Study protocol of a new psychotherapeutic approach for treating pornography use disorder. *Journal of Behavioral Addictions*, *1*(aop). https://doi.org/10.1556/2006.2024.00046

Steele, V. R., Staley, C., Fong, T., & Prause, N. (2013). Sexual desire, not hypersexuality, is related to neurophysiological responses elicited by sexual images. *Socioaffective Neuroscience \& Psychology*, *3*(1), 20770.

Sterling, P. (2012). Allostasis: A model of predictive regulation. *Physiology & Behavior*, *106*(1), 5–15. https://doi.org/10.1016/j.physbeh.2011.06.004

Stewart, D. N., & Szymanski, D. M. (2012). Young Adult Women's Reports of Their Male Romantic Partner's Pornography Use as a Correlate of Their Self-Esteem, Relationship Quality, and Sexual Satisfaction. *Sex Roles*, *67*(5–6), 257–271. https://doi.org/10.1007/S11199-012-0164-0

Straub, J., & Schmidt, C. (2022). A Period of Abstinence from Masturbation and Pornography Leads to Lower Fatigue and Various Other Benefits: A Quantitative Study. *Journal of Addiction Science*, *8*(1). https://doi.org/10.17756/jas.2021-056

Su, Y., Zheng, L., & Zheng, Y. (2023). Pornography Use and Mental Health Problems in the Chinese Population: Examining the Pornography Problems Due to Moral Incongruence Model. *The Journal of Sex Research*, *0*(0), 1–12. https://doi.org/10.1080/00224499.2023.2201255

Subirana, B., Bagiati, A., & Sarma, S. (2017). *On the Forgetting of College Academice: At 'Ebbinghaus Speed'?* [Technical Report]. Center for Brains, Minds and Machines (CBMM). https://dspace.mit.edu/handle/1721.1/110349

Sun, C., Bridges, A., Johnson, J. A., & Ezzell, M. B. (2016). Pornography and the Male Sexual Script: An Analysis of Consumption and Sexual Relations. *Archives of Sexual Behavior*, *45*(4), 983–994. https://doi.org/10.1007/s10508-014-0391-2

Sutton, S. R. (1979). Interpreting relapse curves. *Journal of Consulting and Clinical Psychology*, *47*(1), 96–98. https://doi.org/10.1037/0022-006X.47.1.96

Svedin, C. G., Donevan, M., Bladh, M., Priebe, G., Fredlund, C., & Jonsson, L. S. (2023). Associations between adolescents watching pornography and poor mental health in three Swedish surveys. *European Child & Adolescent Psychiatry*, *32*(9), 1765–1780. https://doi.org/10.1007/s00787-022-01992-x

Szymanski, D., Feltman, C., & Dunn, T. (2015). Male Partners' Perceived Pornography Use and Women's Relational and Psychological Health: The Roles of Trust, Attitudes, and Investment. *Sex Roles*, *73*. https://doi.org/10.1007/s11199-015-0518-5

Takahashi, Y., Uchida, C., Miyaki, K., Sakai, M., Shimbo, T., & Nakayama, T. (2009). Potential benefits and harms of a peer support social network service on the internet for people with depressive tendencies: Qualitative content analysis and social network analysis. *Journal of Medical Internet Research*, *11*(3), e29. https://doi.org/10.2196/jmir.1142

Taleb, N. N. (2022). *Statistical Consequences of Fat Tails: Real World Preasymptotics, Epistemology, and Applications* (No. arXiv:2001.10488). arXiv. https://doi.org/10.48550/arXiv.2001.10488

Tangney, J. P., & Dearing, R. L. (2002). *Shame and guilt* (pp. xvi, 272). Guilford Press. https://doi.org/10.4135/9781412950664.n388

Taverna, Dr. C., Strolego, Dr. I., & Grazia, M. D. (2022). Post-coital dysphoria (pcd): An investigation in male population. *The Journal of Sexual Medicine*, *19*(11, Supplement 4), S81–S82. https://doi.org/10.1016/j.jsxm.2022.10.027

Taylor, K., & Jackson, S. (2018). 'I want that power back': Discourses of masculinity within an online pornography abstinence forum. *Sexualities*, *21*(4), 621–639. https://doi.org/10.1177/1363460717740248

Terracciano, A., Löckenhoff, C. E., Crum, R. M., Bienvenu, O. J., & Costa, P. T. (2008). Five-Factor Model personality profiles of drug users. *BMC Psychiatry*, *8*, 22. https://doi.org/10.1186/1471-244X-8-22

*The 2019 Year in Review – Pornhub Insights*. (2019). https://www.pornhub.com/insights/2019-year-in-review

*The 2021 Year in Review – Pornhub Insights*. (2021). https://www.pornhub.com/insights/yir-2021

Thompson, T., & Schuster, C. R. (1968). *Behavioral pharmacology*. Prentice-Hall.

Tinberge, N. N. (1954). *The study of instinct*. LWW.

Tolomeo, S., & Yu, R. (2022). Brain network dysfunctions in addiction: A meta-analysis of resting-state functional connectivity. *Translational Psychiatry*, *12*(1), 1–11. https://doi.org/10.1038/s41398-022-01792-6

Topno, D. P. M., & Thakurmani, D. (2020). Laughter Induced Syncope: A Case Report. *IOSR Journal of Dental and Medical Sciences (IOSR-JDMS)*, *Volume 19*(Issue 8 Ser.13).

*Truple—Defeat porn & online filth with Screenshot Accountability*. (2022). Truple. https://truple.io/

Tsodyks, M., & Markram, H. (1997). The neural code between neocortical pyramidal neurons depends on neurotransmitter release probability. *Proceedings of the National Academy of Sciences of the United States of America*, *94*(2). https://doi.org/10.1073/pnas.94.2.719

Tuomas, E. (2009). Prediction of multidimensional emotional ratings in music from audio using multivariate regression models. *International Society for Music Information Retrieval Conference (ISMIR), 2009*. https://cir.nii.ac.jp/crid/1573950400595632384

Twohig, M. P., & Crosby, J. M. (2010). Acceptance and commitment therapy as a treatment for problematic internet pornography viewing. *Behavior Therapy*, *41*(3), 285–295.

Twohig, M. P., Crosby, J. M., & Cox, J. M. (2009). Viewing Internet Pornography: For Whom is it Problematic, How, and Why? *Sexual Addiction & Compulsivity*, *16*(4), 253–266. https://doi.org/10.1080/10720160903300788

*uBlock Origin—Free, open-source ad content blocker*. (2022). uBlock Origin. https://ublockorigin.com/

Upton, R. N., & Mould, D. R. (2014). Basic Concepts in Population Modeling, Simulation, and Model-Based Drug Development: Part 3—Introduction to Pharmacodynamic Modeling Methods. *CPT: Pharmacometrics & Systems Pharmacology*, *3*(1), e88. https://doi.org/10.1038/psp.2013.71

Uribe-Bahamonde, Y. E., Becerra, S. A., Ponce, F. P., & Vogel, E. H. (2019). A Quantitative Account of the Behavioral Characteristics of Habituation: The Sometimes Opponent Processes Model of Stimulus Processing. *Frontiers in Psychology*, *10*, 504. https://doi.org/10.3389/fpsyg.2019.00504

Vaillancourt-Morel, M.-P., & Bergeron, S. (2019). Self-perceived problematic pornography use: Beyond individual differences and religiosity. *Archives of Sexual Behavior*, *48*(2), 437–441.

Vaillancourt-Morel, M.-P., Blais-Lecours, S., Labadie, C., Bergeron, S., Sabourin, S., & Godbout, N. (2017). Profiles of Cyberpornography Use and Sexual Well-Being in Adults. *The Journal of Sexual Medicine*, *14*(1), 78–85. https://doi.org/10.1016/j.jsxm.2016.10.016

Vaillancourt-Morel, M.-P., Rosen, N. O., Bőthe, B., & Bergeron, S. (2024). Partner Knowledge of Solitary Pornography Use: Daily and Longitudinal Associations with Relationship Quality. *The Journal of Sex Research*, *61*(8), 1233–1245. https://doi.org/10.1080/00224499.2023.2219254

Vaillancourt-Morel, M.-P., Rosen, N. O., Willoughby, B. J., Leonhardt, N. D., & Bergeron, S. (2020). Pornography use and romantic relationships: A dyadic daily diary study. *Journal of Social and Personal Relationships*, *37*(10–11), 2802–2821. https://doi.org/10.1177/0265407520940048

Venniro, M., Reverte, I., Ramsey, L. A., Papastrat, K. M., D'Ottavio, G., Milella, M. S., Li, X., Grimm, J. W., & Caprioli, D. (2021). Factors modulating the incubation of drug and non-drug craving and their clinical implications. *Neuroscience & Biobehavioral Reviews*, *131*, 847–864. https://doi.org/10.1016/j.neubiorev.2021.09.050

Vescan, M., Flack, M., & Caudwell, K. M. (2024). Loneliness and problematic pornography Use: What is the role of emotion regulation and interaction with content Creators? *Addictive Behaviors Reports*, 100550. https://doi.org/10.1016/j.abrep.2024.100550

Vieira, C., & Griffiths, M. (2024). Problematic Pornography Use and Mental Health: A Systematic Review. *Sexual Health & Compulsivity*. https://doi.org/10.1080/26929953.2024.2348624

Voils, C. I., Chang, Y., Crandell, J., Leeman, J., Sandelowski, M., & Maciejewski, M. L. (2012). Informing the dosing of interventions in randomized trials. *Contemporary Clinical Trials*, *33*(6), 1225–1230. https://doi.org/10.1016/j.cct.2012.07.011

Voils, C. I., King, H. A., Maciejewski, M. L., Allen, K. D., Yancy, W. S., & Shaffer, J. A. (2014). Approaches for Informing Optimal Dose of Behavioral Interventions. *Annals of Behavioral Medicine : A Publication of the Society of Behavioral Medicine*, *48*(3), 392–401. https://doi.org/10.1007/s12160-014-9618-7

Volkow, N. D., Wang, G.-J., Fowler, J. S., Tomasi, D., & Telang, F. (2011). Addiction: Beyond dopamine reward circuitry. *Proceedings of the National Academy of Sciences of the United States of America*, *108*(37), 15037–15042. https://doi.org/10.1073/pnas.1010654108

Voogt, C. V., Kuntsche, E., Kleinjan, M., Poelen, E. A. P., Lemmers, L. A. C. J., & Engels, R. C. M. E. (2013). Using ecological momentary assessment in testing the effectiveness of an alcohol intervention: A two-arm parallel group randomized controlled trial. *PloS One*, *8*(11), e78436.

Voon, V., Mole, T. B., Banca, P., Porter, L., Morris, L., Mitchell, S., Lapa, T. R., Karr, J., Harrison, N. A., Potenza, M. N., & Irvine, M. (2014). Neural Correlates of Sexual Cue Reactivity in Individuals with and without Compulsive Sexual Behaviours. *PLoS ONE*, *9*(7). https://doi.org/10.1371/JOURNAL.PONE.0102419

Wagenmakers, E.-J., Marsman, M., Jamil, T., Ly, A., Verhagen, J., Love, J., Selker, R., Gronau, Q. F., Šmíra, M., Epskamp, S., Matzke, D., Rouder, J. N., & Morey, R. D. (2018). Bayesian inference for psychology. Part I: Theoretical advantages and practical ramifications. *Psychonomic Bulletin & Review*, *25*(1), 35–57. https://doi.org/10.3758/s13423-017-1343-3

Wakefield, J. C. (2012). The DSM-5's Proposed New Categories of Sexual Disorder: The Problem of False Positives in Sexual Diagnosis. *Clinical Social Work Journal*, *40*(2), 213–223. https://doi.org/10.1007/s10615-011-0353-2

Waldinger, M. D., & Schweitzer, D. H. (2002). Postorgasmic Illness Syndrome: Two Cases. *Journal of Sex & Marital Therapy*, *28*(3), 251–255. https://doi.org/10.1080/009262302760328280

Walton, M. T. (2019). Incongruence as a Variable Feature of Problematic Sexual Behaviors in an Online Sample of Self-Reported "Sex Addiction". *Archives of Sexual Behavior*, *48*(2), 443–447. https://doi.org/10.1007/s10508-018-1305-5

Wang, C.-Y., Wu, Y.-C., Su, C.-H., Lin, P.-C., Ko, C.-H., & Yen, J.-Y. (2017). Association between Internet gaming disorder and generalized anxiety disorder. *Journal of Behavioral Addictions*, *6*(4), 564–571. https://doi.org/10.1556/2006.6.2017.088

Watts, S., Mackenzie, A., Thomas, C., Griskaitis, A., Mewton, L., Williams, A., & Andrews, G. (2013). CBT for depression: A pilot RCT comparing mobile phone vs. computer. *BMC Psychiatry*, *13*, 49. https://doi.org/10.1186/1471-244X-13-49

Wehrli, F. S. V., Bodenmann, G. J., Clemen, J., & Weitkamp, K. (2024). Exploring the Role of Masturbation as a Coping Strategy in Women. *International Journal of Sexual Health*, 1–20. https://doi.org/10.1080/19317611.2024.2344812

Wieczorek, Ł., Iwona Klingemann, J., & Badań nad Alkoholizmem Toksykomaniami, Z. (2020). Mobile applications used to limit alcohol consumption – a literature review. *Alcoholism and Drug Addiction/Alkoholizm i Narkomania*, *33*(1), 43–64. https://doi.org/10.5114/AIN.2020.95979

Williams, J. H., Udata, C., Ganguly, B. J., Bucktrout, S. L., Joh, T., Shannon, M., Wong, G. Y., Levisetti, M., Garzone, P. D., & Meng, X. (2020). Model-Based Characterization of the Pharmacokinetics, Target Engagement Biomarkers, and Immunomodulatory Activity of PF-06342674, a Humanized mAb Against IL-7 Receptor-α, in Adults with Type 1 Diabetes. *The AAPS Journal*, *22*(2), 23. https://doi.org/10.1208/s12248-019-0401-3

Willoughby, B. J. (2019). Stuck in the Porn Box. *Archives of Sexual Behavior*, *48*(2), 449–453. https://doi.org/10.1007/s10508-018-1294-4

Willoughby, B. J., Carroll, J. S., Busby, D. M., & Brown, C. C. (2016). Differences in Pornography Use Among Couples: Associations with Satisfaction, Stability, and Relationship Processes. *Archives of Sexual Behavior*, *45*(1), 145–158. https://doi.org/10.1007/s10508-015-0562-9

Willoughby, B. J., & Dover, C. R. (2022). Context Matters: Moderating Effects in the Associations between Pornography Use, Perceived Addiction, and Relationship Well-being. *The Journal of Sex Research*, *0*(0), 1–14. https://doi.org/10.1080/00224499.2022.2148155

Winters, J. (2010). Hypersexual Disorder: A More Cautious Approach. *Archives of Sexual Behavior*, *39*(3), 594–596. https://doi.org/10.1007/s10508-010-9607-2

Witkiewitz, K., & Marlatt, G. A. (2007). Modeling the complexity of post-treatment drinking: It's a rocky road to relapse. *Clinical Psychology Review*, *27*(6), 724–738.

Wixted, J. T., & Ebbesen, E. B. (1991). On the Form of Forgetting. *Psychological Science*, *2*(6), 409–415. https://doi.org/10.1111/j.1467-9280.1991.tb00175.x

Wolak, J., Mitchell, K., & Finkelhor, D. (2007). Unwanted and wanted exposure to online pornography in a national sample of youth Internet users. *Pediatrics*, *119*(2), 247–257.

Wordecha, M., Wilk, M., Kowalewska, E., Skorko, M., Łapiński, A., & Gola, M. (2018). Pornographic binges as a key characteristic of males seeking treatment for compulsive sexual behaviors: Qualitative and quantitative 10-week-long diary assessment. *Journal of Behavioral Addictions*, *7*(2), 433–444.

Wright, P. J. (2012). A Longitudinal Analysis of US Adults' Pornography Exposure. *Journal of Media Psychology*, *24*(2), 67–76. https://doi.org/10.1027/1864-1105/a000063

Wright, P. J. (2013). A Three-Wave Longitudinal Analysis of Preexisting Beliefs, Exposure to Pornography, and Attitude Change. *Communication Reports*, *26*(1), 13–25. https://doi.org/10.1080/08934215.2013.773053

Wright, P. J. (2019). Dysregulated Pornography Use and the Possibility of a Unipathway Approach. *Archives of Sexual Behavior*, *48*(2), 455–460. https://doi.org/10.1007/s10508-018-1277-5

Wright, P. J. (2023). Pornography Consumption and Extramarital Sex Attitudes Among Married U.S. Adults: Longitudinal Replication. *Archives of Sexual Behavior*, *52*(5), 1953–1960. https://doi.org/10.1007/s10508-023-02612-8

Wright, P. J., Tokunaga, R. S., Kraus, A., & Klann, E. (2017). Pornography consumption and satisfaction: A meta-analysis. *Human Communication Research*, *43*(3), 315–343.

Wrzus, C., & Neubauer, A. B. (2022). Ecological Momentary Assessment: A Meta-Analysis on Designs, Samples, and Compliance Across Research Fields. *Assessment*, 10731911211067538. https://doi.org/10.1177/10731911211067538

*X3watch—Internet Porn Accountability Software*. (2022). X3watch. https://x3watch.com/

Yim, J. (2016). Therapeutic Benefits of Laughter in Mental Health: A Theoretical Review. *The Tohoku Journal of Experimental Medicine*, *239*(3), 243–249. https://doi.org/10.1620/tjem.239.243

Young, K., Pistner, M., O'MARA, J., & Buchanan, J. (1999). Cyber disorders: The mental health concern for the new millennium. *Cyberpsychology \& Behavior*, *2*(5), 475–479.

Zhang, N., Hazarika, B., Chen, K., & Shi, Y. (2023). A cross-national study on the excessive use of short-video applications among college students. *Computers in Human Behavior*, *145*, 107752. https://doi.org/10.1016/j.chb.2023.107752

Zhu, Y., Hu, C.-X., Liu, X., Zhu, R.-X., & Wang, B.-Q. (2023). Moderate coffee or tea consumption decreased the risk of cognitive disorders: An updated dose–response meta-analysis. *Nutrition Reviews*, nuad089. https://doi.org/10.1093/nutrit/nuad089

Zitzman, S. T., & Butler, M. H. (2009). Wives' experience of husbands' pornography use and concomitant deception as an attachment threat in the adult pair-bond relationship. *Sexual Addiction \& Compulsivity*, *16*(3), 210–240.

Zou, H., Banerjee, P., Leung, S. S. Y., & Yan, X. (2020). Application of Pharmacokinetic-Pharmacodynamic Modeling in Drug Delivery: Development and Challenges. *Frontiers in Pharmacology*, *11*, 997. https://doi.org/10.3389/fphar.2020.00997

## Appendices

Additional online Appendices can be found on the Open Science Framework website at the following link: https://osf.io/ck597/ (N. Henry, 2024a). These include the R code for the behavioural posology study, a selection of R code used to create the Bayesian hierarchical mixed effects models in the IPU study[19], an ethics approval letter from AUTEC for the IPU study, the participant information sheet and advertisement for the IPU study, and data dictionaries for both the pre-EMA survey in REDCap and the EMA surveys in SEMA3.

[19] Due to ethical requirements, we are unable to share the data for this study publicly.

**Appendix A**

**Additional Descriptive Statistics for IPU Study**

Table A1 contains additional descriptive statistics that were not included in the body of the main article.

A very strong correlation was detected between responses to the question 'How important is religion in your life?' and higher moral incongruence scores for masturbation with pornography use ($r = 0.70$, $p = 0.0032$), as well as strong correlations with moral incongruence scores for pornography use by itself ($r = 0.60$, $p = 0.0029$) and with moral incongruence scores for masturbation by itself ($r = 0.67$, $p = 0.0006$).

A moderate correlation was detected between participants' PPCS-6 scores (measuring PPU tendencies) and their ULS-8 loneliness scores ($r = 0.47$, $p = 0.027$) and HADS depression scores ($r = 0.47$, $p = 0.028$). I did not find evidence for a correlation between PPCS-6 scores and MFI mental fatigue scores ($r = 0.43$, $p = 0.051$), HADS anxiety scores ($r = 0.30$, $p = 0.18$), GSES shame scores ($r = 0.42$, $p = 0.053$) or GSES guilt scores ($r = 0.36$, $p = 0.10$).

For participants with high moral incongruence, the mean score for moral incongruence regarding pornography use combined with masturbation (5.60) was significantly higher than the mean score for moral incongruence regarding masturbation alone (3.40, $p = 0.0098$). For low moral incongruence participants, the difference was not significant (1.00 vs 0.33, $p = 0.14$).

*Table A1: Additional demographic data for 22 participants who contributed data to EMA, divided by level of moral incongruence with respect to pornography use with masturbation.*

| Variable | High moral incongruence, N = 10 | Low moral incongruence, N = 12 |
|---|---|---|
| Currently active member of any online or in-person groups to reduce pornography use or masturbation frequency | 6 (60%) | 8 (67%) |
| Total relationship satisfaction score (0-8) | 3.67 (0.58) | 5.00 (1.00) |
| Marital status | | |
| Married/civil union/de facto | 1 (10%) | 1 (8.3%) |
| Separated/divorced/widowed | 1 (10%) | 0 (0%) |
| Never married (single) | 8 (80%) | 11 (92%) |
| Prefer not to say | 0 (0%) | 0 (0%) |
| Highest level of education | | |
| Primary school/Elementary school | 0 (0%) | 0 (0%) |
| Intermediate school/Middle school | 0 (0%) | 0 (0%) |

| Variable | High moral incongruence, N = 10 | Low moral incongruence, N = 12 |
| --- | --- | --- |
| High school | 0 (0%) | 2 (17%) |
| Trade or technical qualification | 0 (0%) | 0 (0%) |
| Diploma or certificate | 0 (0%) | 0 (0%) |
| University/college (undergraduate) | 8 (80%) | 8 (67%) |
| University/college (postgraduate) | 2 (20%) | 2 (17%) |
| Employment status | | |
| Full-time: Paid employment for >=30 hrs a week | 4 (40%) | 6 (50%) |
| Part-time: Paid employment for 1 to less than 30 hrs a week | 1 (10%) | 3 (25%) |
| Not in paid employment or paid employment for less than 1 hour per week | 5 (50%) | 3 (25%) |
| Retired | 0 (0%) | 0 (0%) |
| Online groups/forums used (can select more than one) | | |
| r/nofap, r/nofapteens or r/nofapchristians on reddit.com or nofap.com | 1 (10%) | 4 (27%) |
| r/pornfree or r/pornfreewomen on reddit.com | 6 (60%) | 8 (53%) |
| Fight The New Drug (FTND) - fightthenewdrug.org | 3 (30%) | 0 (0%) |
| Your Brain On Porn (YBOP) - yourbrainonporn.com | 0 (0%) | 1 (7%) |
| Sexaholics Anonymous | 0 (0%) | 0 (0%) |
| Other | 0 (0%) | 2 (13%) |
| Currently using an app/software to help reduce pornography use or masturbation frequency | 6 (60%) | 4 (36%) |
| Reason for using app/software (can select more than one) | | |
| To block sexual content on the Internet or my device | 4 (31%) | 2 (25%) |
| To access tutorials/coaching sessions to help me reduce pornography use/masturbation | 2 (15%) | 0 (0%) |
| To keep track of my 'streak length' (i.e. how long since I last used pornography/masturbated | 4 (31%) | 2 (25%) |
| To connect with an 'accountability buddy' who checks my progress reducing pornography use/masturbation | 1 (8%) | 1 (12%) |
| To keep track of my mental health over time (e.g. tracking mood, anxiety or stress levels on a daily basis | 0 (0%) | 0 (0%) |
| To keep track of my financial savings from not using pornography | 0 (0%) | 1 (12%) |

| Variable | High moral incongruence, N = 10 | Low moral incongruence, N = 12 |
|---|---|---|
| To distract me from using pornography or masturbating (e.g. through playing games, meditating, or using a 'panic button' | 2 (15%) | 1 (12%) |
| Other | 0 (0%) | 1 (12%) |
| Total HADS depression score (0-21) | 6.30 (5.14) | 8.08 (4.48) |
| Total HADS anxiety score (0-21) | 9.00 (3.83) | 9.58 (4.19) |
| Total MFI score (4-20) | 13.10 (2.64) | 13.55 (4.16) |
| Total BSDS score (0-4) | 1.67 (1.41) | 1.67 (0.89) |
| Total GSES score (8-32) | 23.20 (3.79) | 22.08 (5.74) |
| Total ULS-8 score (8-32) | 22.70 (6.68) | 21.17 (7.54) |
| Total PPCS-6 score (6-42) | 30.10 (5.17) | 29.33 (10.71) |
| Moral incongruence score for pornography use without masturbation | | |
| 0 - Not at all | 0 (0%) | 7 (58%) |
| 1 | 0 (0%) | 2 (17%) |
| 2 | 0 (0%) | 0 (0%) |
| 3 - Somewhat | 0 (0%) | 2 (17%) |
| 4 | 2 (20%) | 1 (8.3%) |
| 5 | 3 (30%) | 0 (0%) |
| 6 - Very strongly | 5 (50%) | 0 (0%) |
| Moral incongruence score for masturbation without pornography use | | |
| 0 - Not at all | 1 (10%) | 9 (75%) |
| 1 | 1 (10%) | 2 (17%) |
| 2 | 1 (10%) | 1 (8.3%) |
| 3 - Somewhat | 3 (30%) | 0 (0%) |
| 4 | 1 (10%) | 0 (0%) |
| 5 | 0 (0%) | 0 (0%) |
| 6 - Very strongly | 3 (30%) | 0 (0%) |
| Moral incongruence score for masturbation with pornography use | | |
| 0 - Not at all | 0 (0%) | 7 (58%) |
| 1 | 0 (0%) | 1 (8.3%) |
| 2 | 0 (0%) | 1 (8.3%) |
| 3 - Somewhat | 0 (0%) | 3 (25%) |
| 4 | 1 (10%) | 0 (0%) |
| 5 | 2 (20%) | 0 (0%) |
| 6 - Very strongly | 7 (70%) | 0 (0%) |

## Appendix B

### Model Parameters Produced by Bayesian Analysis in IPU Study

Table B1 contains all model parameters produced from attempting to fit hierarchical exponential models to mental health scores obtained pre- and post-sexual episode via Bayesian modelling.

Group A: any episodes of pornography use, either with or without masturbation or orgasm. Group B: any episodes of pornography use, either with or without masturbation or orgasm, plus episodes of masturbation without pornography use.

*Table B1: Model parameters produced from Bayesian modelling process. For the final column, Bayesian t-tests were only performed if the Bayes Factor in favour of the exponential model was greater than 1 for either of the low or high moral incongruence levels.*

| Wellbeing variable | Pre- or post-episode | Type of sexual episode | Truncation | Moral incongruence level | a, amplitude of exponential model [95% CI] | b, decay constant of exponential model [95% CI] | c, offset of exponential model [95% CI] | d, intercept of linear model [95% CI] | Posterior probability for exponential model | Posterior probability for linear model | Bayes Factor in favour of exponential model | Bayes Factor in favour of difference in effect sizes between high and low moral incongruence participants |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Anxiety | Post-episode | Group A | No | High moral incongruence | -0.01203 [-0.826, 0.9178] | -5.792 [-9.795, -1.29] | 3.335 [2.406, 4.206] | 3.364 [2.523, 4.243] | 0.6746 | 0.3254 | 2.058 | |
| | | | | Low moral incongruence | -0.4159 [-3.095, 1.553] | -1.391 [-9.082, -0.005781] | 3.916 [2.551, 6.068] | 3.592 [2.646, 4.583] | 0.07733 | 0.9227 | 0.1344 | |
| | | | Yes | High moral incongruence | -0.4567 [-1.359, 0.7951] | -5.03 [-9.675, -1.627] | 3.383 [2.5, 4.617] | 3.437 [2.435, 4.54] | 0.0003521 | 0.9996 | 0.003605 | |
| | | | | Low moral incongruence | 0.2441 [-0.9095, 1.418] | -5.497 [-9.788, -0.2771] | 3.281 [2.13, 4.475] | 3.328 [2.216, 4.499] | 0.02648 | 0.9735 | 0.02613 | |
| | | Group B | No | High moral incongruence | -0.9653 [-3.775, 0.9046] | -5.935 [-9.743, -1.366] | 2.939 [1.947, 4.233] | 3.284 [2.373, 4.242] | 0.00277 | 0.9972 | 0.001998 | |
| | | | | Low moral incongruence | -0.7496 [-3.806, 1.114] | -0.7219 [-7.749, -0.002917] | 4.323 [3.161, 7.29] | 3.67 [2.71, 4.602] | 0.3027 | 0.6973 | 0.4372 | |
| | | | Yes | High moral incongruence | 0.1105 [-0.9454, 2.218] | -6.049 [-9.746, -1.296] | 4.251 [2.533, 8.174] | 3.4 [2.291, 4.486] | 4.898e-11 | 1 | 3.785e-11 | |

| Wellbeing variable | Pre- or post-episode | Type of sexual episode | Truncation | Moral incongruence level | a, amplitude of exponential model [95% CI] | b, decay constant of exponential model [95% CI] | c, offset of exponential model [95% CI] | d, intercept of linear model [95% CI] | Posterior probability for exponential model | Posterior probability for linear model | Bayes Factor in favour of exponential model | Bayes Factor in favour of difference in effect sizes between high and low moral incongruence participants |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Low moral incongruence | 0.2648 [-0.8464, 1.668] | -4.665 [-9.79, -0.08545] | 3.46 [2.378, 4.671] | 3.537 [2.44, 4.737] | 0.02118 | 0.9788 | 0.02236 | |
| | Pre-episode | Group A | No | High moral incongruence | 1.231 [-0.8743, 4.306] | 6.613 [2.458, 9.775] | 2.998 [2.176, 3.815] | 3.076 [2.208, 3.911] | 1.189e-09 | 1 | 2.466e-12 | |
| | | | | Low moral incongruence | -1.637 [-4.49, 2.455] | 5.783 [0.6323, 9.828] | 3.634 [2.462, 4.78] | 3.581 [2.416, 4.748] | 0.1914 | 0.8086 | 0.2171 | |
| | | | Yes | High moral incongruence | 2.009 [-1.322, 4.586] | 6.362 [2.008, 9.778] | 3.192 [2.361, 4.095] | 3.269 [2.457, 4.074] | 0.3237 | 0.6763 | 0.5114 | |
| | | | | Low moral incongruence | -2.338 [-4.76, 2.345] | 4.146 [0.02348, 9.662] | 3.899 [2.278, 6.265] | 3.394 [2.185, 4.677] | 0.0659 | 0.9341 | 0.07003 | |
| | | Group B | No | High moral incongruence | 2.03 [-0.7734, 4.578] | 6.672 [2.462, 9.856] | 2.961 [2.044, 3.887] | 3.015 [2.165, 3.883] | 0.3468 | 0.6532 | 0.5513 | |
| | | | | Low moral incongruence | -1.624 [-4.186, 1.106] | 5.011 [0.3194, 9.709] | 3.645 [2.49, 4.845] | 3.629 [2.437, 4.806] | 0.2149 | 0.7851 | 0.2614 | |
| | | | Yes | High moral incongruence | 2.113 [-0.6413, 4.559] | 6.414 [2.204, 9.806] | 3.228 [2.363, 4.11] | 3.292 [2.436, 4.111] | 0.3298 | 0.6702 | 0.4897 | 2.498e+06 |
| | | | | Low moral incongruence | -2.422 [-4.624, -0.06111] | 0.3105 [0.01727, 1.31] | 4.602 [3.252, 6.363] | 3.451 [2.305, 4.663] | 0.8512 | 0.1488 | 4.289 | |
| Craving for pornography | Post-episode | Group A | No | High moral incongruence | -0.4289 [-1.155, 0.475] | -6.268 [-9.781, -1.486] | 1.812 [0.93, 2.828] | 1.73 [0.8883, 2.683] | 0.04485 | 0.9551 | 0.0495 | 0.1622 |

| Wellbeing variable | Pre- or post-episode | Type of sexual episode | Truncation | Moral incongruence level | a, amplitude of exponential model [95% CI] | b, decay constant of exponential model [95% CI] | c, offset of exponential model [95% CI] | d, intercept of linear model [95% CI] | Posterior probability for exponential model | Posterior probability for linear model | Bayes Factor in favour of exponential model | Bayes Factor in favour of difference in effect sizes between high and low moral incongruence participants |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Low moral incongruence | 0.8358 [-0.9106, 2.468] | -6.489 [-9.865, -1.598] | 1.855 [0.8435, 2.746] | 2.006 [1.134, 2.838] | 0.5791 | 0.4209 | 1.319 | |
| | | | Yes | High moral incongruence | -1.251 [-3.605, 0.3634] | -6.604 [-9.8, -1.674] | 1.898 [0.7925, 2.926] | 1.634 [0.6537, 2.758] | 0.001983 | 0.998 | 0.0008047 | 0.1430 |
| | | | | Low moral incongruence | 1.276 [-0.715, 3.124] | -6.349 [-9.817, -1.254] | 1.578 [0.7187, 2.424] | 1.895 [0.9913, 2.745] | 0.9658 | 0.03421 | 29.96 | |
| | | Group B | No | High moral incongruence | -0.3894 [-1.114, 0.4838] | -6.328 [-9.827, -1.652] | 1.74 [0.7223, 2.686] | 1.689 [0.8812, 2.597] | 0.03839 | 0.9616 | 0.0433 | 302.4 |
| | | | | Low moral incongruence | 0.8592 [-0.6968, 2.65] | -5.221 [-9.745, -0.4178] | 2.083 [1.26, 2.883] | 2.271 [1.376, 3.253] | 0.6587 | 0.3413 | 2.081 | |
| | | | Yes | High moral incongruence | -0.4112 [-1.148, 0.4776] | -6.293 [-9.874, -1.39] | 1.78 [0.7488, 2.872] | 1.649 [0.6451, 2.672] | 0.03459 | 0.9654 | 0.03339 | 180.8 |
| | | | | Low moral incongruence | 1.38 [-0.3887, 3.27] | -5.965 [-9.864, -0.4192] | 1.637 [0.8015, 2.559] | 2.089 [1.139, 3.147] | 0.9929 | 0.007084 | 144.9 | |
| | Pre-episode | Group A | No | High moral incongruence | -1.192 [-3.713, 3.203] | 5.089 [1.254, 9.831] | 2.272 [1.409, 3.781] | 2.406 [1.339, 3.504] | 0.002731 | 0.9973 | 0.00198 | |
| | | | | Low moral incongruence | -0.4949 [-4.482, 4.148] | 6.498 [1.318, 9.843] | 2.233 [1.172, 3.293] | 2.168 [1.111, 3.209] | 0.0953 | 0.9047 | 0.09702 | |
| | | | Yes | High moral incongruence | 0.001788 [-3.112, 3.287] | 5.526 [0.3182, 9.82] | 1.624 [0.608, 2.467] | 1.528 [0.6456, 2.433] | 0.04923 | 0.9508 | 0.04778 | |
| | | | | Low moral incongruence | -0.173 [-4.532, 3.183] | 6.194 [1.646, 9.823] | 3.707 [1.233, 8.049] | 2.162 [1.045, 3.238] | 0.001014 | 0.999 | 0.0008458 | |

| Wellbeing variable | Pre- or post-episode | Type of sexual episode | Truncation | Moral incongruence level | a, amplitude of exponential model [95% CI] | b, decay constant of exponential model [95% CI] | c, offset of exponential model [95% CI] | d, intercept of linear model [95% CI] | Posterior probability for exponential model | Posterior probability for linear model | Bayes Factor in favour of exponential model | Bayes Factor in favour of difference in effect sizes between high and low moral incongruence participants |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Group B | No | High moral incongruence | -0.4473 [-3.923, 3.156] | 6.382 [1.469, 9.875] | 2.474 [1.335, 3.563] | 2.399 [1.265, 3.524] | 0.07992 | 0.9201 | 0.08083 | |
| | | | | Low moral incongruence | -0.9331 [-4.082, 2.541] | 6.177 [1.043, 9.89] | 2.337 [1.18, 3.394] | 2.323 [1.322, 3.336] | 0.1108 | 0.8892 | 0.1159 | |
| | | | Yes | High moral incongruence | -0.02741 [-3.968, 3.442] | 6.051 [0.8168, 9.837] | 1.515 [0.6431, 2.423] | 1.486 [0.5931, 2.331] | 0.06981 | 0.9302 | 0.07558 | |
| | | | | Low moral incongruence | -1.548 [-4.426, 2.449] | 5.824 [1.304, 9.768] | 2.233 [1.256, 3.264] | 2.113 [1.041, 3.128] | 0.2638 | 0.7362 | 0.3668 | |
| Craving for sexual intercourse | Post-episode | Group A | No | High moral incongruence | 0.2309 [-1.041, 1.57] | -6.266 [-9.85, -1.201] | 2.235 [1.124, 3.43] | 2.284 [1.128, 3.441] | 0.1144 | 0.8856 | 0.1442 | |
| | | | | Low moral incongruence | 0.7529 [-0.5491, 2.279] | -6.612 [-9.842, -1.691] | 2.451 [1.043, 3.823] | 2.57 [1.306, 3.902] | 0.05828 | 0.9417 | 0.06575 | |
| | | | Yes | High moral incongruence | 0.6557 [-0.7952, 2.102] | -5.639 [-9.774, -0.515] | 1.842 [0.467, 3.216] | 1.947 [0.645, 3.23] | 0.7758 | 0.2242 | 3.815 | 65.36 |
| | | | | Low moral incongruence | -0.21 [-3.178, 2.232] | -4.345 [-9.729, -1.801] | 4.379 [1.268, 7.259] | 2.52 [1.132, 3.91] | 0 | 1 | 0 | |
| | | Group B | No | High moral incongruence | 0.2515 [-1.012, 1.538] | -6.194 [-9.847, -1.159] | 2.205 [1.108, 3.453] | 2.249 [1.074, 3.424] | 0.1186 | 0.8814 | 0.1393 | |
| | | | | Low moral incongruence | 0.7921 [-0.4177, 2.346] | -6.935 [-9.873, -2.25] | 2.724 [1.416, 4.126] | 2.891 [1.606, 4.262] | 0.07012 | 0.9299 | 0.0748 | |
| | | | Yes | High moral incongruence | 1.215 [-0.6588, 2.491] | -5.16 [-9.664, -0.3789] | 2.079 [0.6182, 3.06] | 1.968 [0.7175, 3.251] | 0.00157 | 0.9984 | 3.249e-05 | |

| Wellbeing variable | Pre- or post-episode | Type of sexual episode | Truncation | Moral incongruence level | a, amplitude of exponential model [95% CI] | b, decay constant of exponential model [95% CI] | c, offset of exponential model [95% CI] | d, intercept of linear model [95% CI] | Posterior probability for exponential model | Posterior probability for linear model | Bayes Factor in favour of exponential model | Bayes Factor in favour of difference in effect sizes between high and low moral incongruence participants |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Low moral incongruence | -0.2053 [-3.184, 2.497] | -5.396 [-9.721, -2.347] | 2.446 [1.434, 3.694] | 2.85 [1.538, 4.265] | 7.209e-06 | 1 | 5.503e-06 | |
| | Pre-episode | Group A | No | High moral incongruence | -0.363 [-3.763, 3.139] | 6.281 [1.509, 9.873] | 2.842 [1.487, 4.32] | 2.732 [1.448, 4.072] | 0.1236 | 0.8764 | 0.1396 | |
| | | | | Low moral incongruence | -0.008891 [-3.968, 4.065] | 6.507 [1.444, 9.824] | 2.608 [1.364, 3.892] | 2.576 [1.377, 3.859] | 0.08151 | 0.9185 | 0.0819 | |
| | | | Yes | High moral incongruence | -1.413 [-4.556, 2.726] | 2.931 [0.07491, 8.936] | 2.369 [0.9962, 3.839] | 2.018 [0.6405, 3.378] | 0.4958 | 0.5042 | 1.328 | 2.487e+04 |
| | | | | Low moral incongruence | -0.8358 [-4.453, 3.313] | 6.024 [0.8623, 9.865] | 2.412 [0.952, 3.869] | 2.343 [0.9425, 3.65] | 0.09063 | 0.9094 | 0.1085 | |
| | | Group B | No | High moral incongruence | -0.2982 [-3.61, 3.195] | 6.233 [1.663, 9.835] | 2.76 [1.378, 4.242] | 2.716 [1.434, 4.018] | 0.1204 | 0.8796 | 0.1261 | |
| | | | | Low moral incongruence | 0.2765 [-3.205, 3.788] | 6.637 [1.542, 9.854] | 2.696 [1.442, 4.01] | 2.675 [1.544, 3.823] | 0.05667 | 0.9433 | 0.0536 | |
| | | | Yes | High moral incongruence | -1.338 [-4.016, 2.266] | 3.035 [0.1456, 8.971] | 2.346 [0.9265, 3.771] | 2.007 [0.7483, 3.295] | 0.4281 | 0.5719 | 0.8164 | |
| | | | | Low moral incongruence | -0.5023 [-3.662, 2.802] | 6.238 [1.307, 9.835] | 2.428 [0.9215, 3.759] | 2.383 [1.071, 3.717] | 0.05405 | 0.946 | 0.05518 | |
| Difficulty thinking | Post-episode | Group A | No | High moral incongruence | 0.7668 [-0.4421, 2.153] | -4.92 [-9.58, -1.31] | 3.045 [2.109, 4] | 3.163 [2.363, 4.014] | 0.9983 | 0.00171 | 618.7 | 0.2327 |
| | | | | Low moral incongruence | 0.7129 [0.01498, 1.711] | -6.128 [-9.667, -1.038] | 5.018 [3.073, 8.2] | 4.121 [3.221, 5.089] | 0.008011 | 0.992 | 0.00481 | |

| Wellbeing variable | Pre- or post-episode | Type of sexual episode | Truncation | Moral incongruence level | a, amplitude of exponential model [95% CI] | b, decay constant of exponential model [95% CI] | c, offset of exponential model [95% CI] | d, intercept of linear model [95% CI] | Posterior probability for exponential model | Posterior probability for linear model | Bayes Factor in favour of exponential model | Bayes Factor in favour of difference in effect sizes between high and low moral incongruence participants |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Yes | High moral incongruence | -0.2936 [-3.021, 1.751] | -4.513 [-9.685, -1.543] | 4.092 [2.246, 6.986] | 3.276 [2.29, 4.217] | 0.03997 | 0.96 | 0.02297 | |
| | | | | Low moral incongruence | 0.8653 [-0.1707, 1.927] | -5.698 [-9.773, -0.9363] | 4.106 [3.016, 5.16] | 4.317 [3.326, 5.299] | 0.05306 | 0.9469 | 0.05534 | |
| | | Group B | No | High moral incongruence | 1.167 [-0.2868, 2.479] | -3.475 [-9.713, -0.4207] | 2.827 [1.859, 3.734] | 3.128 [2.302, 4.026] | 0.9995 | 0.0004702 | 2765 | 0.1699 |
| | | | | Low moral incongruence | 1.268 [-0.4625, 2.86] | -2.966 [-8.756, -0.3931] | 3.754 [2.63, 4.884] | 4.123 [3.298, 4.985] | 1 | 2.839e-05 | 33400 | |
| | | | Yes | High moral incongruence | 0.6406 [-0.5516, 2.118] | -5.609 [-9.74, -1.484] | 3.141 [2.065, 4.247] | 3.305 [2.373, 4.192] | 0.9597 | 0.04033 | 23.52 | 6.108 |
| | | | | Low moral incongruence | 0.5415 [-2.926, 2.656] | -2.467 [-6.751, -0.7086] | 3.74 [1.858, 7.09] | 4.232 [3.432, 5.059] | 0 | 1 | 0 | |
| | Pre-episode | Group A | No | High moral incongruence | 1.572 [-2.647, 4.598] | 5.977 [1.246, 9.811] | 2.727 [1.665, 3.8] | 2.697 [1.717, 3.7] | 0.4007 | 0.5993 | 0.7018 | 0.2044 |
| | | | | Low moral incongruence | 2.871 [-1.838, 4.89] | 5.304 [1.568, 9.693] | 3.723 [2.702, 4.789] | 3.806 [2.841, 4.81] | 0.9086 | 0.09138 | 8.491 | |
| | | | Yes | High moral incongruence | 1.409 [-2.611, 4.646] | 6.257 [1.603, 9.811] | 3.021 [1.844, 4.205] | 3.187 [2.054, 4.321] | 0.2666 | 0.7334 | 0.375 | 0.4328 |
| | | | | Low moral incongruence | 2.756 [-1.788, 4.897] | 5.871 [1.77, 9.695] | 3.986 [2.682, 5.261] | 4.066 [2.948, 5.202] | 0.6389 | 0.3611 | 1.728 | |
| | | Group B | No | High moral incongruence | 1.889 [-2.52, 4.445] | 5.995 [1.929, 9.771] | 2.679 [1.642, 3.675] | 2.699 [1.651, 3.734] | 0.4814 | 0.5186 | 0.8637 | 0.5430 |
| | | | | Low moral incongruence | 2.919 [-1.498, 4.917] | 4.245 [1.028, 9.28] | 3.678 [2.817, 4.552] | 3.797 [3.057, 4.535] | 1 | 2.416e-06 | 390900 | |

| Wellbeing variable | Pre- or post-episode | Type of sexual episode | Truncation | Moral incongruence level | a, amplitude of exponential model [95% CI] | b, decay constant of exponential model [95% CI] | c, offset of exponential model [95% CI] | d, intercept of linear model [95% CI] | Posterior probability for exponential model | Posterior probability for linear model | Bayes Factor in favour of exponential model | Bayes Factor in favour of difference in effect sizes between high and low moral incongruence participants |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Yes | High moral incongruence | 1.309 [-3.165, 4.437] | 6.155 [1.708, 9.828] | 2.998 [1.855, 4.076] | 3.104 [1.974, 4.197] | 0.2661 | 0.7339 | 0.3791 | 1.188 |
| | | | | Low moral incongruence | 2.67 [-2.424, 4.89] | 4.152 [0.6997, 9.316] | 3.661 [1.974, 5.081] | 4.037 [3.1, 4.982] | 1 | 1.582e-05 | 68560 | |
| Guilt | Post-episode | Group A | No | High moral incongruence | 2.649 [1.267, 4.156] | -5.066 [-9.665, -1.155] | 3.581 [1.706, 5.551] | 4.014 [2.386, 5.653] | 1 | 2.04e-18 | 1.412e+18 | 27.32 |
| | | | | Low moral incongruence | 0.7152 [-0.7556, 2.131] | -5.835 [-9.829, -0.1084] | 3.669 [1.814, 5.568] | 3.854 [2.024, 5.632] | 0.8831 | 0.1169 | 6.158 | |
| | | | Yes | High moral incongruence | 3.224 [1.778, 4.799] | -1.29 [-8.077, -0.02202] | 2.731 [0.657, 4.945] | 4.427 [2.727, 6.181] | 1 | 2.162e-14 | 1.04e+14 | 87.47 |
| | | | | Low moral incongruence | 0.7237 [-0.649, 1.943] | -6.395 [-9.864, -1.308] | 3.669 [1.635, 5.875] | 3.985 [1.932, 6.123] | 0.2573 | 0.7427 | 0.3218 | |
| | | Group B | No | High moral incongruence | 1.257 [-3.076, 4.124] | -5.243 [-9.442, -1.355] | 3.37 [1.785, 5.365] | 3.939 [2.394, 5.529] | 1 | 5.972e-06 | 16580 | 577.6 |
| | | | | Low moral incongruence | 0.8909 [-0.3472, 2.235] | -5.888 [-9.715, -0.6753] | 3.862 [2.03, 5.759] | 4.07 [2.133, 5.845] | 0.9848 | 0.01518 | 77.99 | |
| | | | Yes | High moral incongruence | 2.645 [1.061, 4.241] | -4.555 [-9.935, -0.3873] | 3.547 [1.689, 5.701] | 4.399 [2.61, 6.185] | 1 | 2.031e-17 | 1.264e+16 | 93.37 |
| | | | | Low moral incongruence | 0.3413 [-1.49, 1.978] | -5.26 [-9.81, -1.616] | 3.513 [2.221, 5.743] | 4.213 [2.419, 6.091] | 0.00107 | 0.9989 | 0.000919 | |
| | Pre-episode | Group A | No | High moral incongruence | 1.842 [-2.2, 4.636] | 5.476 [0.09674, 9.711] | 3.047 [1.613, 4.606] | 3.28 [1.917, 4.649] | 0.305 | 0.695 | 0.7724 | |

| Wellbeing variable | Pre- or post-episode | Type of sexual episode | Truncation | Moral incongruence level | a, amplitude of exponential model [95% CI] | b, decay constant of exponential model [95% CI] | c, offset of exponential model [95% CI] | d, intercept of linear model [95% CI] | Posterior probability for exponential model | Posterior probability for linear model | Bayes Factor in favour of exponential model | Bayes Factor in favour of difference in effect sizes between high and low moral incongruence participants |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Low moral incongruence | 0.3195 [-3.869, 3.993] | 6.554 [1.518, 9.843] | 3.898 [2.044, 5.856] | 3.876 [2.034, 5.627] | 0.1109 | 0.8891 | 0.1204 | |
| | | | Yes | High moral incongruence | 1.273 [-3.202, 4.693] | 6.185 [1.896, 9.762] | 3.701 [1.759, 5.767] | 3.717 [2.043, 5.467] | 0.712 | 0.288 | 2.802 | 0.4366 |
| | | | | Low moral incongruence | -0.6034 [-3.444, 3.788] | 5.131 [1.129, 9.793] | 3.906 [1.667, 5.547] | 3.649 [1.693, 5.634] | 6.563e-05 | 0.9999 | 4.967e-05 | |
| | | Group B | No | High moral incongruence | 2.213 [-0.7617, 4.338] | 3.656 [0.2434, 8.945] | 4.37 [1.73, 8.68] | 3.239 [1.876, 4.632] | 1.639e-18 | 1 | 1.665e-17 | |
| | | | | Low moral incongruence | 0.2669 [-2.623, 3.243] | 6.415 [1.156, 9.857] | 3.867 [2.198, 5.687] | 3.861 [2.076, 5.6] | 0.04854 | 0.9515 | 0.04366 | |
| | | | Yes | High moral incongruence | 2.272 [-2.181, 4.755] | 3.703 [0.4221, 9.473] | 2.899 [1.096, 5.062] | 3.617 [1.937, 5.222] | 0.9412 | 0.05881 | 11.82 | 4.004 |
| | | | | Low moral incongruence | 0.2 [-2.508, 2.792] | 6.084 [0.4103, 9.837] | 3.63 [1.521, 5.65] | 3.593 [1.591, 5.441] | 0.04102 | 0.959 | 0.04271 | |
| Loneliness | Post-episode | Group A | No | High moral incongruence | 0.5245 [-0.3632, 1.822] | -4.395 [-9.568, -1.63] | 5.456 [2.717, 8.395] | 4.087 [2.756, 5.432] | 0 | 1 | 0 | |
| | | | | Low moral incongruence | 0.2891 [-0.7427, 1.233] | -5.998 [-9.831, -1.097] | 4.292 [2.504, 6.296] | 4.345 [2.711, 6.05] | 0.04238 | 0.9576 | 0.0324 | |
| | | | Yes | High moral incongruence | 1.05 [0.1993, 1.95] | -5.952 [-9.797, -1.367] | 3.94 [2.425, 5.494] | 4.263 [2.893, 5.865] | 0.9561 | 0.04395 | 19.91 | 0.3004 |
| | | | | Low moral incongruence | 0.4599 [-0.5527, 1.375] | -6.106 [-9.859, -0.9897] | 4.203 [2.49, 6.074] | 4.338 [2.677, 5.989] | 0.04052 | 0.9595 | 0.04064 | |

| Wellbeing variable | Pre- or post-episode | Type of sexual episode | Truncation | Moral incongruence level | a, amplitude of exponential model [95% CI] | b, decay constant of exponential model [95% CI] | c, offset of exponential model [95% CI] | d, intercept of linear model [95% CI] | Posterior probability for exponential model | Posterior probability for linear model | Bayes Factor in favour of exponential model | Bayes Factor in favour of difference in effect sizes between high and low moral incongruence participants |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Group B | No | High moral incongruence | 1.231 [0.2654, 2.35] | -4.376 [-9.698, -0.02286] | 3.667 [2.062, 5.141] | 3.968 [2.627, 5.245] | 0.9989 | 0.001128 | 714.6 | 1.004 |
| | | | | Low moral incongruence | 0.2701 [-0.7366, 1.238] | -6.183 [-9.841, -1.033] | 4.746 [2.766, 6.521] | 4.702 [2.855, 6.42] | 0.03919 | 0.9608 | 0.04033 | |
| | | | Yes | High moral incongruence | 0.9811 [0.1824, 1.847] | -6.08 [-9.817, -1.476] | 3.934 [2.348, 5.471] | 4.316 [2.893, 5.751] | 0.9305 | 0.06953 | 14.43 | 0.1229 |
| | | | | Low moral incongruence | 1.266 [-0.2916, 3.729] | -5.243 [-9.825, -1.629] | 5.303 [2.955, 6.874] | 4.675 [2.749, 6.489] | 1.346e-06 | 1 | 3.976e-07 | |
| | Pre-episode | Group A | No | High moral incongruence | 1.785 [-2.818, 4.677] | 6.967 [2.457, 9.864] | 3.437 [1.962, 4.818] | 3.477 [2.092, 4.839] | 0.4606 | 0.5394 | 0.8664 | |
| | | | | Low moral incongruence | 1.387 [-3.166, 4.646] | 6.687 [1.972, 9.881] | 4.345 [2.373, 6.323] | 4.364 [2.623, 6.11] | 0.2192 | 0.7808 | 0.2781 | |
| | | | Yes | High moral incongruence | 1.467 [-2.657, 4.623] | 6.899 [2.064, 9.901] | 4.122 [2.453, 5.897] | 4.22 [2.734, 5.902] | 0.2466 | 0.7534 | 0.3618 | |
| | | | | Low moral incongruence | 1.551 [-3.09, 4.497] | 5.348 [1.743, 9.833] | 4.046 [2.286, 6.106] | 4.227 [2.285, 6.102] | 1.571e-05 | 1 | 0.0001744 | |
| | | Group B | No | High moral incongruence | 1.751 [-2.581, 4.669] | 6.897 [2.264, 9.905] | 3.395 [1.971, 4.823] | 3.404 [1.988, 4.757] | 0.438 | 0.562 | 0.7734 | |
| | | | | Low moral incongruence | 1.003 [-2.564, 4.313] | 6.496 [1.599, 9.862] | 4.197 [2.328, 5.977] | 4.133 [2.417, 5.82] | 0.1062 | 0.8938 | 0.1154 | |
| | | | Yes | High moral incongruence | 1.315 [-2.939, 4.52] | 6.925 [2.253, 9.898] | 4.079 [2.425, 5.687] | 4.225 [2.628, 5.82] | 0.263 | 0.737 | 0.3452 | |
| | | | | Low moral incongruence | -0.06193 [-2.775, 3.998] | 5.332 [1.804, 9.783] | 4.467 [2.209, 6.158] | 3.967 [2.133, 5.691] | 0.001514 | 0.9985 | 0.000988 | |

| Wellbeing variable | Pre- or post-episode | Type of sexual episode | Truncation | Moral incongruence level | a, amplitude of exponential model [95% CI] | b, decay constant of exponential model [95% CI] | c, offset of exponential model [95% CI] | d, intercept of linear model [95% CI] | Posterior probability for exponential model | Posterior probability for linear model | Bayes Factor in favour of exponential model | Bayes Factor in favour of difference in effect sizes between high and low moral incongruence participants |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Mood | Post-episode | Group A | No | High moral incongruence | -1.411 [-2.798, -0.09054] | -5.992 [-9.775, -2.469] | 5.128 [4.532, 5.609] | 4.941 [4.355, 5.408] | 1 | 1.088e-05 | 92020 | 0.354 |
| | | | | Low moral incongruence | -0.03277 [-1.474, 1.701] | -4.831 [-9.722, -0.9072] | 4.673 [3.419, 5.895] | 4.95 [4.087, 5.768] | 0.08467 | 0.9153 | 0.1078 | |
| | | | Yes | High moral incongruence | -1.153 [-2.561, 0.007609] | -6.767 [-9.799, -2.714] | 4.836 [3.828, 5.622] | 4.546 [3.622, 5.399] | 0.9862 | 0.01384 | 66.57 | 1881 |
| | | | | Low moral incongruence | -0.7531 [-2.255, 0.638] | -3.463 [-9.702, -0.04331] | 5.122 [4.179, 6.156] | 4.838 [3.898, 5.81] | 0.5285 | 0.4715 | 1.093 | |
| | | Group B | No | High moral incongruence | 0.1077 [-2.428, 1.982] | -4.426 [-9.488, -1.81] | 5.32 [2.583, 8.459] | 4.972 [4.358, 5.499] | 0 | 1 | 0 | 0.1480 |
| | | | | Low moral incongruence | -0.6221 [-1.489, 0.1921] | -5.904 [-9.832, -0.6308] | 4.99 [4.231, 5.716] | 4.881 [4.186, 5.569] | 0.4872 | 0.5128 | 1.019 | |
| | | | Yes | High moral incongruence | -0.4255 [-2.625, 2.059] | -6.049 [-9.711, -3.098] | 4.602 [3.71, 5.62] | 4.56 [3.539, 5.42] | 0.7837 | 0.2163 | 7.091 | 254.1 |
| | | | | Low moral incongruence | -0.692 [-1.923, 0.3008] | -4.698 [-9.794, -0.04241] | 5.111 [4.238, 6.095] | 4.786 [3.974, 5.612] | 0.3386 | 0.6614 | 0.4082 | |
| | Pre-episode | Group A | No | High moral incongruence | -2.237 [-4.479, 1.445] | 6.078 [1.52, 9.864] | 4.574 [2.104, 5.928] | 5.373 [4.891, 5.96] | 4.705e-09 | 1 | 7.916e-11 | |
| | | | | Low moral incongruence | -0.161 [-3.998, 4.057] | 6.039 [1.035, 9.863] | 5.03 [4.331, 5.83] | 5.08 [4.323, 5.86] | 0.134 | 0.866 | 0.1468 | |
| | | | Yes | High moral incongruence | -2.074 [-4.819, 2.428] | 7.662 [3.8, 9.91] | 5.054 [4.204, 5.798] | 4.933 [4.201, 5.549] | 0.9785 | 0.02145 | 45.03 | 0.9398 |

| Wellbeing variable | Pre- or post-episode | Type of sexual episode | Truncation | Moral incongruence level | a, amplitude of exponential model [95% CI] | b, decay constant of exponential model [95% CI] | c, offset of exponential model [95% CI] | d, intercept of linear model [95% CI] | Posterior probability for exponential model | Posterior probability for linear model | Bayes Factor in favour of exponential model | Bayes Factor in favour of difference in effect sizes between high and low moral incongruence participants |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Low moral incongruence | 0.6011 [-3.869, 3.545] | 5.272 [0.8013, 9.752] | 5.034 [4.096, 5.873] | 5.014 [4.127, 5.914] | 0.01077 | 0.9892 | 0.01128 | |
| | | Group B | No | High moral incongruence | -1.866 [-4.613, 1.964] | 7.7 [3.737, 9.911] | 5.401 [4.888, 5.948] | 5.358 [4.827, 5.846] | 0.6312 | 0.3688 | 1.664 | 0.2100 |
| | | | | Low moral incongruence | -0.3627 [-3.19, 2.21] | 6.735 [1.859, 9.884] | 5.056 [4.397, 5.821] | 5.116 [4.418, 5.791] | 0.05791 | 0.9421 | 0.04847 | |
| | | | Yes | High moral incongruence | -2.054 [-4.825, 2.335] | 7.724 [3.905, 9.93] | 5.018 [4.16, 5.723] | 4.917 [4.206, 5.496] | 0.9626 | 0.03739 | 29.04 | |
| | | | | Low moral incongruence | -0.6027 [-3.588, 2.751] | 6.755 [1.588, 9.873] | 5.093 [4.176, 5.945] | 5.085 [4.305, 5.831] | 0.0498 | 0.9502 | 0.05436 | |
| Relationship connectedness | Post-episode | Group A | No | High moral incongruence | -1.024 [-1.819, -0.3107] | -2.471 [-8.025, -0.4102] | 4.648 [3.565, 5.687] | 4.446 [3.414, 5.437] | 1 | 3.778e-05 | 27280 | 0.1710 |
| | | | | Low moral incongruence | -0.6639 [-1.257, 0.2637] | -4.703 [-9.755, -0.6927] | 3.935 [1.968, 6.55] | 4.364 [2.427, 6.454] | 2.52e-07 | 1 | 6.354e-08 | |
| | | | Yes | High moral incongruence | -1.006 [-1.624, -0.4599] | -3.087 [-8.956, -0.3914] | 4.744 [3.663, 6.064] | 4.347 [3.321, 5.328] | 0.9993 | 0.0006944 | 1503 | 1.229 |
| | | | | Low moral incongruence | -0.259 [-1, 0.4821] | -5.882 [-9.761, -0.9006] | 4.412 [2.368, 6.498] | 4.304 [2.258, 6.219] | 0.004292 | 0.9957 | 0.004458 | |
| | | Group B | No | High moral incongruence | -1.092 [-1.878, -0.3406] | -2.852 [-8.227, -0.4503] | 4.664 [3.556, 5.773] | 4.462 [3.379, 5.449] | 1 | 6.886e-06 | 132400 | 0.2536 |
| | | | | Low moral incongruence | -0.4334 [-1.044, 0.1537] | -6.11 [-9.803, -1.163] | 4.349 [2.09, 6.504] | 4.325 [2.419, 6.332] | 0.004923 | 0.9951 | 0.005027 | |

| Wellbeing variable | Pre- or post-episode | Type of sexual episode | Truncation | Moral incongruence level | a, amplitude of exponential model [95% CI] | b, decay constant of exponential model [95% CI] | c, offset of exponential model [95% CI] | d, intercept of linear model [95% CI] | Posterior probability for exponential model | Posterior probability for linear model | Bayes Factor in favour of exponential model | Bayes Factor in favour of difference in effect sizes between high and low moral incongruence participants |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Yes | High moral incongruence | -1.881 [-2.749, -0.5877] | -4.522 [-8.572, -0.5814] | 5.686 [3.812, 6.738] | 4.376 [3.259, 5.411] | 0 | 1 | 0 | 23.73 |
| | | | | Low moral incongruence | 0.1672 [-0.7383, 1.519] | -5.193 [-9.69, -1.38] | 4.904 [2.729, 8.22] | 4.208 [2.309, 6.201] | 0 | 1 | 0 | |
| | Pre-episode | Group A | No | High moral incongruence | -1.732 [-4.462, 1.671] | 4.187 [1.046, 9.172] | 4.937 [3.917, 5.981] | 4.765 [3.662, 5.767] | 0.9848 | 0.01517 | 78.38 | 0.2949 |
| | | | | Low moral incongruence | -1.348 [-4.625, 3.69] | 5.832 [1.203, 9.841] | 4.24 [2.054, 6.426] | 4.268 [2.318, 6.233] | 0.2939 | 0.7061 | 0.3557 | |
| | | | Yes | High moral incongruence | -1.5 [-4.362, 1.609] | 4.431 [1.005, 9.502] | 4.521 [3.304, 5.681] | 4.273 [3.044, 5.525] | 0.4749 | 0.5251 | 0.9693 | |
| | | | | Low moral incongruence | -1.763 [-4.226, 2.957] | 4.847 [1.564, 9.677] | 5.496 [1.956, 8.223] | 4.355 [2.1, 6.83] | 3.7e-58 | 1 | 2.802e-55 | |
| | | Group B | No | High moral incongruence | -1.624 [-4.501, 2.299] | 4.382 [1.187, 9.123] | 4.865 [3.843, 5.92] | 4.761 [3.696, 5.753] | 0.988 | 0.01202 | 81.84 | 0.4077 |
| | | | | Low moral incongruence | -0.2767 [-3.403, 3.118] | 6.852 [1.705, 9.899] | 4.448 [2.166, 6.636] | 4.41 [2.311, 6.477] | 0.02061 | 0.9794 | 0.02041 | |
| | | | Yes | High moral incongruence | -1.513 [-4.46, 2.126] | 4.568 [1.045, 9.519] | 4.487 [3.244, 5.767] | 4.283 [3.124, 5.462] | 0.5045 | 0.4955 | 1.053 | 0.1871 |
| | | | | Low moral incongruence | -0.3054 [-3.3, 2.861] | 6.617 [1.375, 9.901] | 4.503 [1.996, 6.746] | 4.599 [2.268, 7.093] | 0.02586 | 0.9741 | 0.02436 | |
| Shame | Post-episode | Group A | No | High moral incongruence | 2.369 [1.074, 3.727] | -5.033 [-9.569, -1.348] | 3.587 [1.843, 5.686] | 3.948 [2.446, 5.626] | 1 | 4.173e-16 | 1.95e+15 | 1.409 |
| | | | | Low moral incongruence | 0.778 [-0.6014, 2.051] | -6.456 [-9.833, -1.731] | 3.654 [1.845, 5.528] | 3.81 [1.888, 5.792] | 0.3273 | 0.6727 | 0.4511 | |

| Wellbeing variable | Pre- or post-episode | Type of sexual episode | Truncation | Moral incongruence level | a, amplitude of exponential model [95% CI] | b, decay constant of exponential model [95% CI] | c, offset of exponential model [95% CI] | d, intercept of linear model [95% CI] | Posterior probability for exponential model | Posterior probability for linear model | Bayes Factor in favour of exponential model | Bayes Factor in favour of difference in effect sizes between high and low moral incongruence participants |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Yes | High moral incongruence | 3.498 [1.753, 4.893] | -0.06233 [-0.1543, -0.01501] | 1.912 [0.2264, 4.034] | 4.218 [2.663, 6.01] | 1 | 1.006e-11 | 7.291e+10 | 1.468 |
| | | | | Low moral incongruence | 0.6594 [-0.6905, 1.844] | -6.395 [-9.804, -1.408] | 3.733 [1.579, 6.09] | 3.979 [1.781, 6.017] | 0.1798 | 0.8202 | 0.2107 | |
| | | Group B | No | High moral incongruence | 2.469 [1.066, 3.858] | -4.999 [-9.545, -1.332] | 3.516 [1.771, 5.36] | 3.879 [2.229, 5.492] | 1 | 1.463e-18 | 8.259e+17 | 21.04 |
| | | | | Low moral incongruence | 0.9436 [-0.02548, 2.027] | -6.382 [-9.828, -1.674] | 3.836 [1.967, 5.667] | 4.133 [2.218, 6.09] | 0.9026 | 0.09736 | 9.354 | |
| | | | Yes | High moral incongruence | 1.845 [-0.1324, 4.137] | -4.028 [-9.274, -0.09831] | 4.581 [1.564, 8.263] | 4.249 [2.624, 5.897] | 5.798e-08 | 1 | 7.567e-09 | 4.738 |
| | | | | Low moral incongruence | 0.8474 [-0.2472, 1.846] | -6.377 [-9.868, -1.614] | 3.939 [1.88, 5.951] | 4.132 [2.109, 5.968] | 0.7793 | 0.2207 | 3.856 | |
| | Pre-episode | Group A | No | High moral incongruence | 1.432 [-3.359, 4.675] | 5.415 [1.244, 9.792] | 3.467 [1.97, 5.049] | 3.517 [1.998, 4.963] | 0.9955 | 0.004458 | 233.2 | 0.2031 |
| | | | | Low moral incongruence | 1.181 [-3.124, 4.596] | 6.72 [1.77, 9.879] | 3.926 [1.963, 5.934] | 3.974 [2.209, 5.825] | 0.1494 | 0.8506 | 0.1651 | |
| | | | Yes | High moral incongruence | 1.404 [-3.132, 4.66] | 5.152 [0.9446, 9.759] | 3.578 [1.565, 5.587] | 3.778 [1.995, 5.555] | 0.8685 | 0.1315 | 7.559 | 0.1784 |
| | | | | Low moral incongruence | 1.154 [-2.859, 4.564] | 6.494 [1.372, 9.85] | 3.652 [1.2, 5.876] | 3.687 [1.709, 5.724] | 0.1439 | 0.8561 | 0.167 | |
| | | Group B | No | High moral incongruence | 2.365 [-0.5954, 4.695] | 2.974 [0.3495, 7.913] | 3.184 [1.556, 4.803] | 3.46 [2.025, 4.941] | 1 | 3.697e-06 | 259100 | 0.5748 |

| Wellbeing variable | Pre- or post-episode | Type of sexual episode | Truncation | Moral incongruence level | a, amplitude of exponential model [95% CI] | b, decay constant of exponential model [95% CI] | c, offset of exponential model [95% CI] | d, intercept of linear model [95% CI] | Posterior probability for exponential model | Posterior probability for linear model | Bayes Factor in favour of exponential model | Bayes Factor in favour of difference in effect sizes between high and low moral incongruence participants |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Low moral incongruence | 1.25 [-1.803, 3.974] | 6.809 [1.758, 9.873] | 3.691 [1.64, 5.403] | 3.607 [1.751, 5.436] | 0.1057 | 0.8943 | 0.1107 | |
| | | | Yes | High moral incongruence | 2.321 [-1.572, 4.812] | 2.797 [0.2255, 8.604] | 3.036 [1.041, 5.215] | 3.616 [1.98, 5.347] | 0.9378 | 0.06218 | 19.88 | 0.3853 |
| | | | | Low moral incongruence | 1.024 [-2.385, 3.954] | 6.622 [1.67, 9.886] | 3.44 [1.346, 5.67] | 3.396 [1.446, 5.173] | 0.08441 | 0.9156 | 0.09102 | |

## Appendix C

## Graphs of Temporal Dynamics in IPU Study

Below are all graphs produced from fitting hierarchical exponential models to mental health scores obtained pre- and post-sexual episode via Bayesian modelling. Only the 24 hours before and after sexual episodes are displayed. Graphs on the left are for low moral incongruence participants, while graphs on the right are for high moral incongruence participants. Error ribbons represent 95% credible intervals. Exponential models are presented in cases where $BF_{10} > 1$, indicating evidence in favour of the alternative hypothesis, while horizontal models indicate cases where $BF_{01} > 1$, indicating evidence in favour of the null hypothesis.

Group A: any episodes of pornography use, either with or without masturbation or orgasm. Group B: any episodes of pornography use, either with or without masturbation or orgasm, plus episodes of masturbation without pornography use.

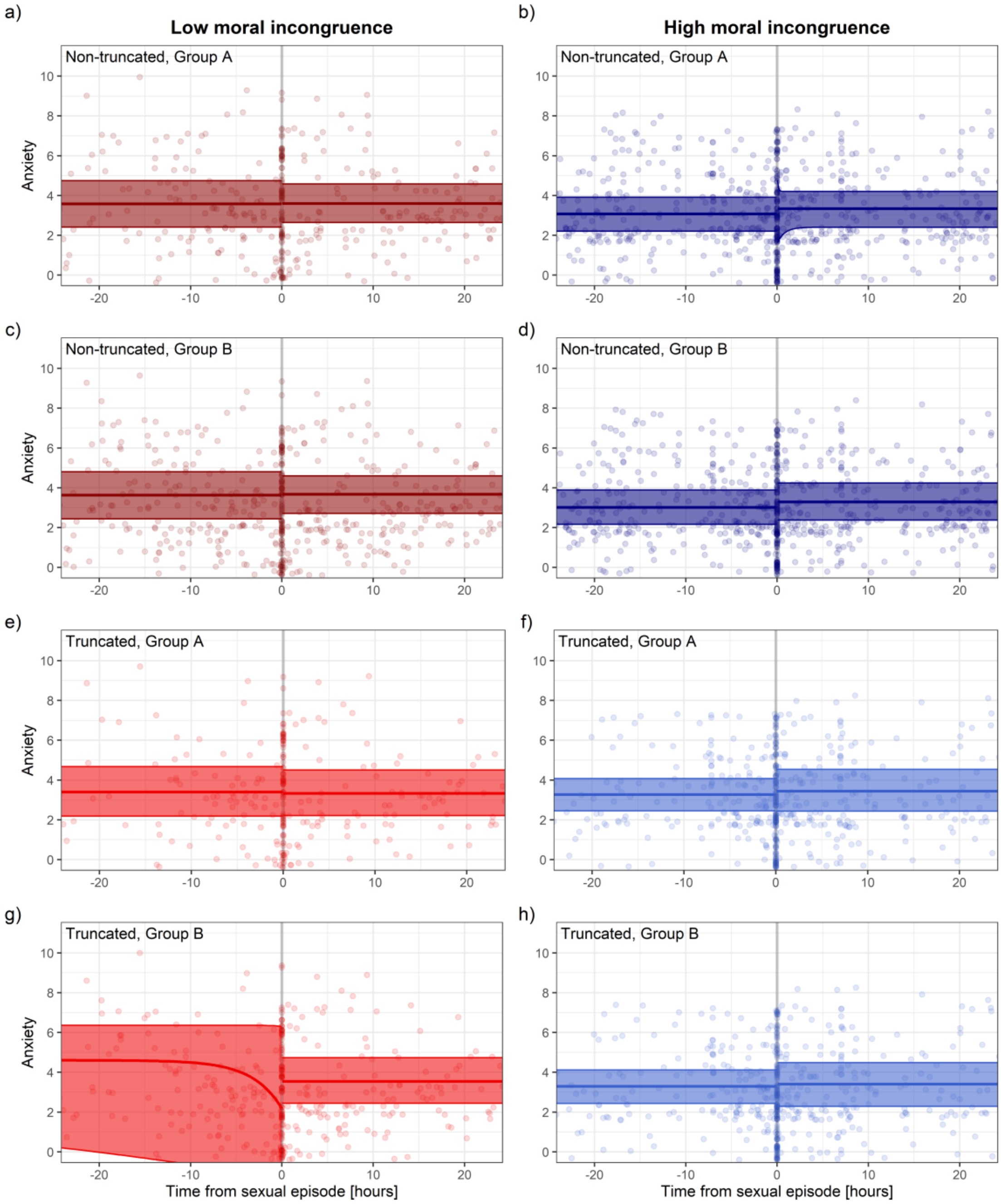


*Figure C1: Results from fitting hierarchical exponential models to 'anxiety' scores obtained pre- and post-sexual episodes, showing 24 hours before and after episodes.*

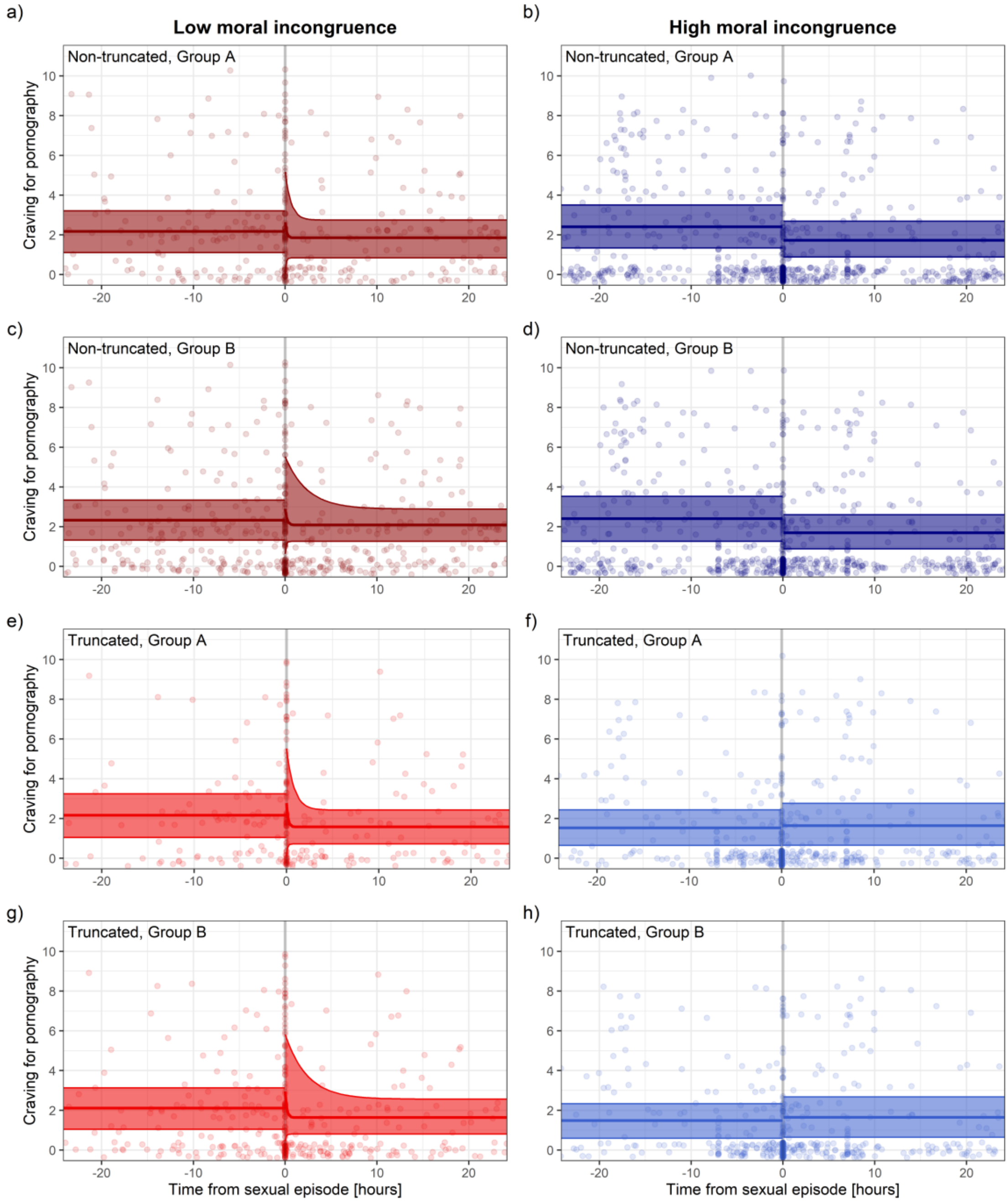


*Figure C2: Results from fitting hierarchical exponential models to 'craving for pornography' scores obtained pre- and post-sexual episodes, showing 24 hours before and after episodes.*

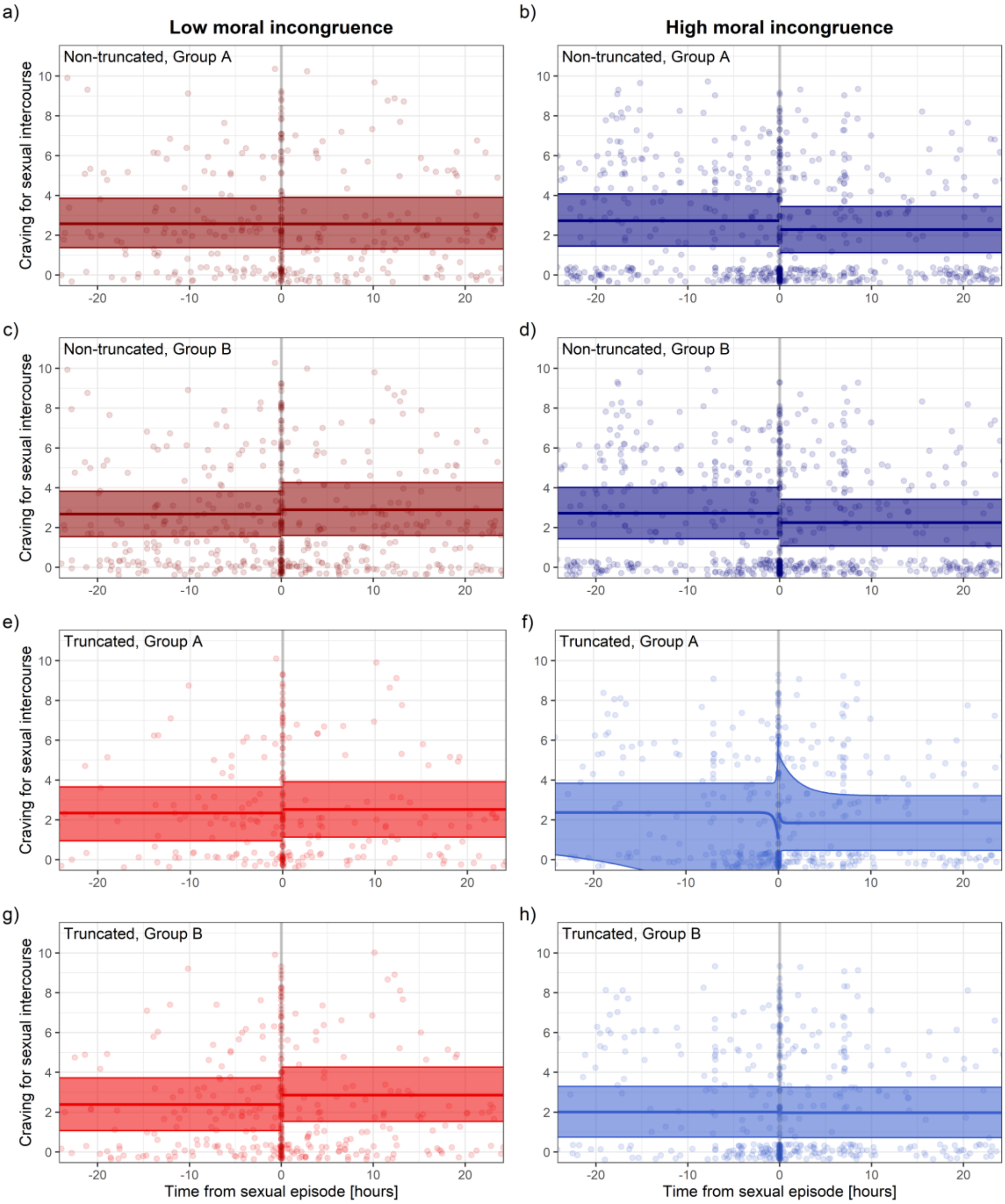


*Figure C3: Results from fitting hierarchical exponential models to 'craving for sexual intercourse' scores obtained pre- and post-sexual episodes, showing 24 hours before and after episodes.*

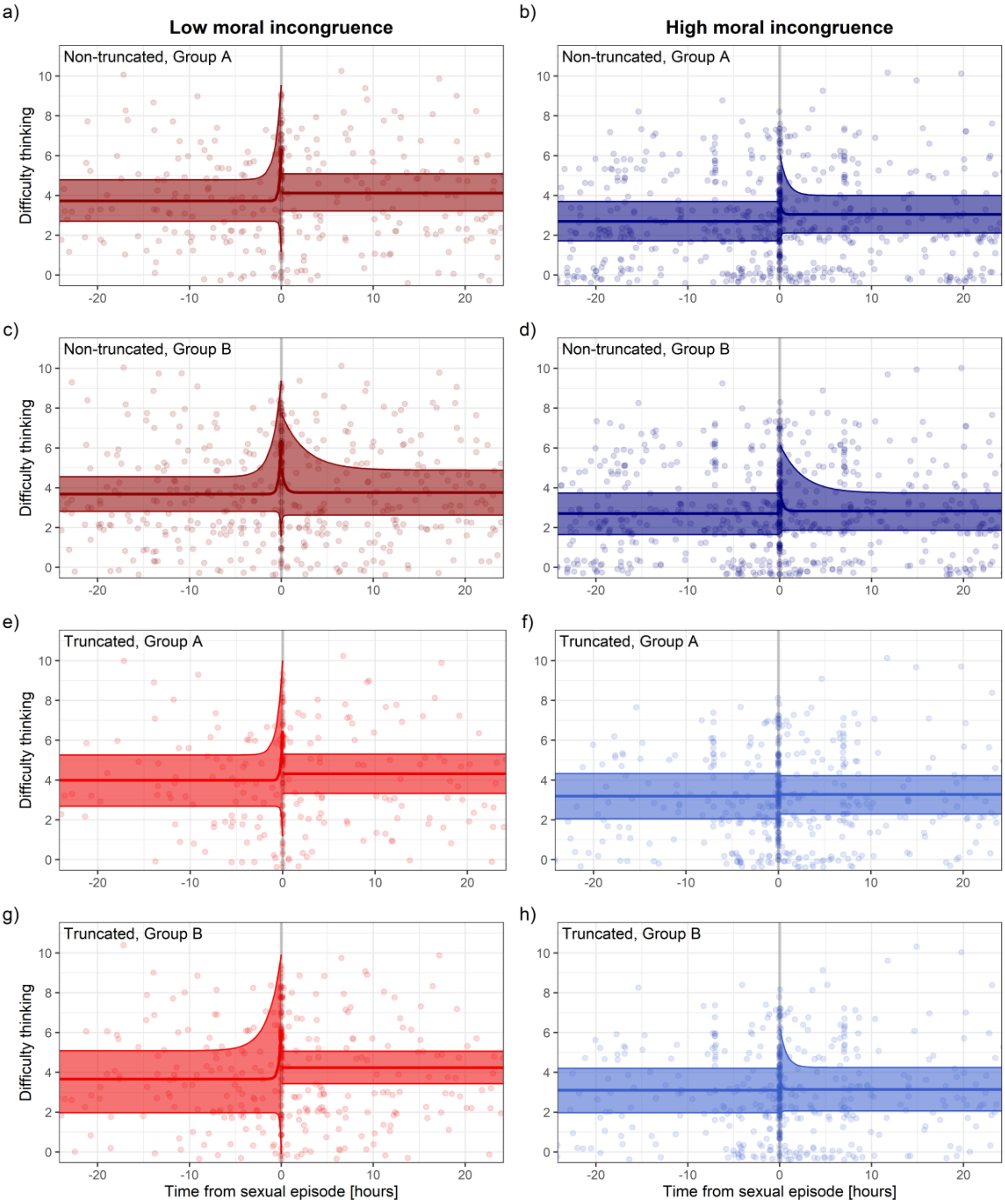


*Figure C4: Results from fitting hierarchical exponential models to 'difficulty thinking' scores obtained pre- and post-sexual episodes, showing 24 hours before and after episodes.*

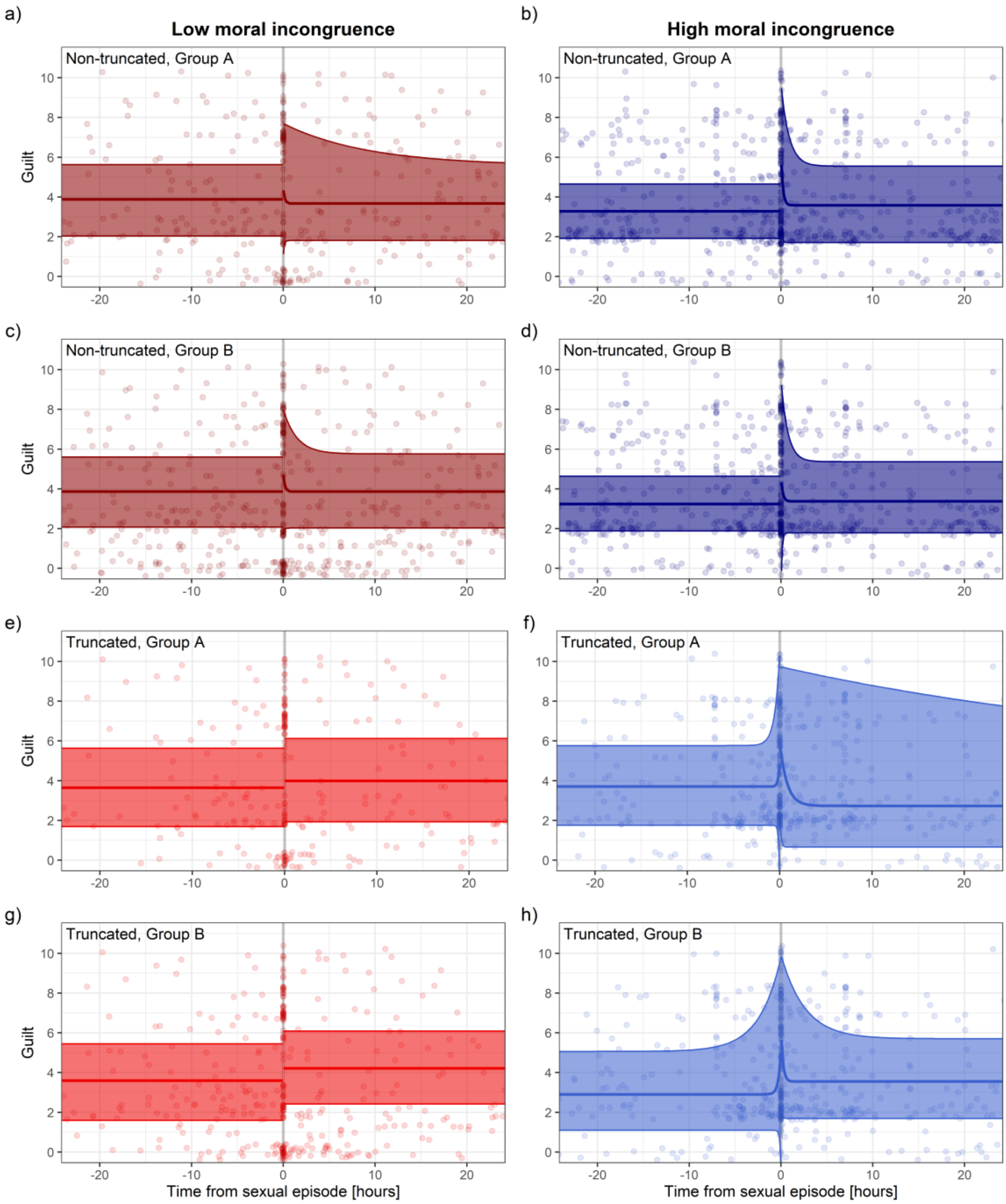


*Figure C5: Results from fitting hierarchical exponential models to 'guilt' scores obtained pre- and post-sexual episodes, showing 24 hours before and after episodes.*

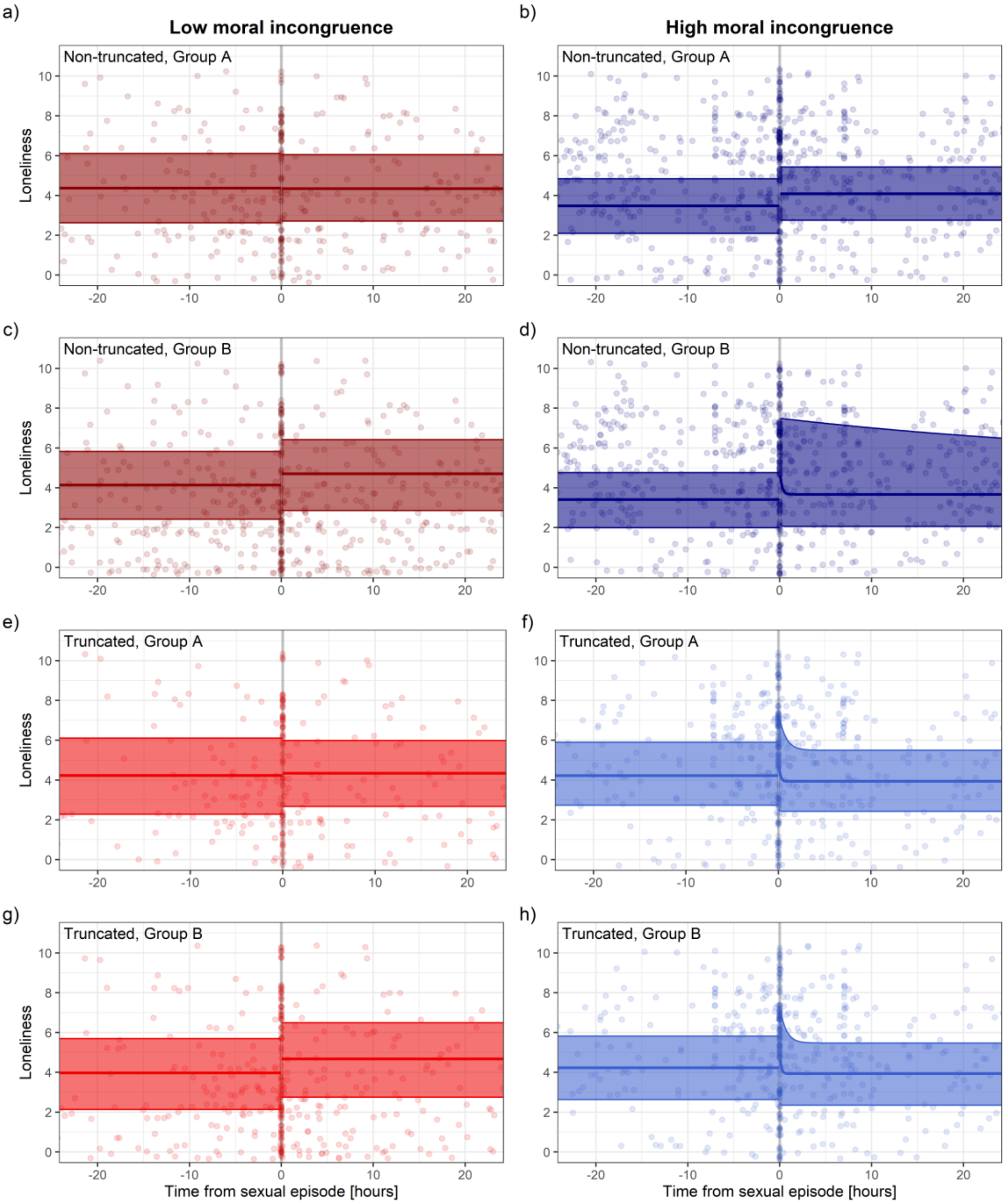


*Figure C6: Results from fitting hierarchical exponential models to 'loneliness' scores obtained pre- and post-sexual episodes, showing 24 hours before and after episodes.*

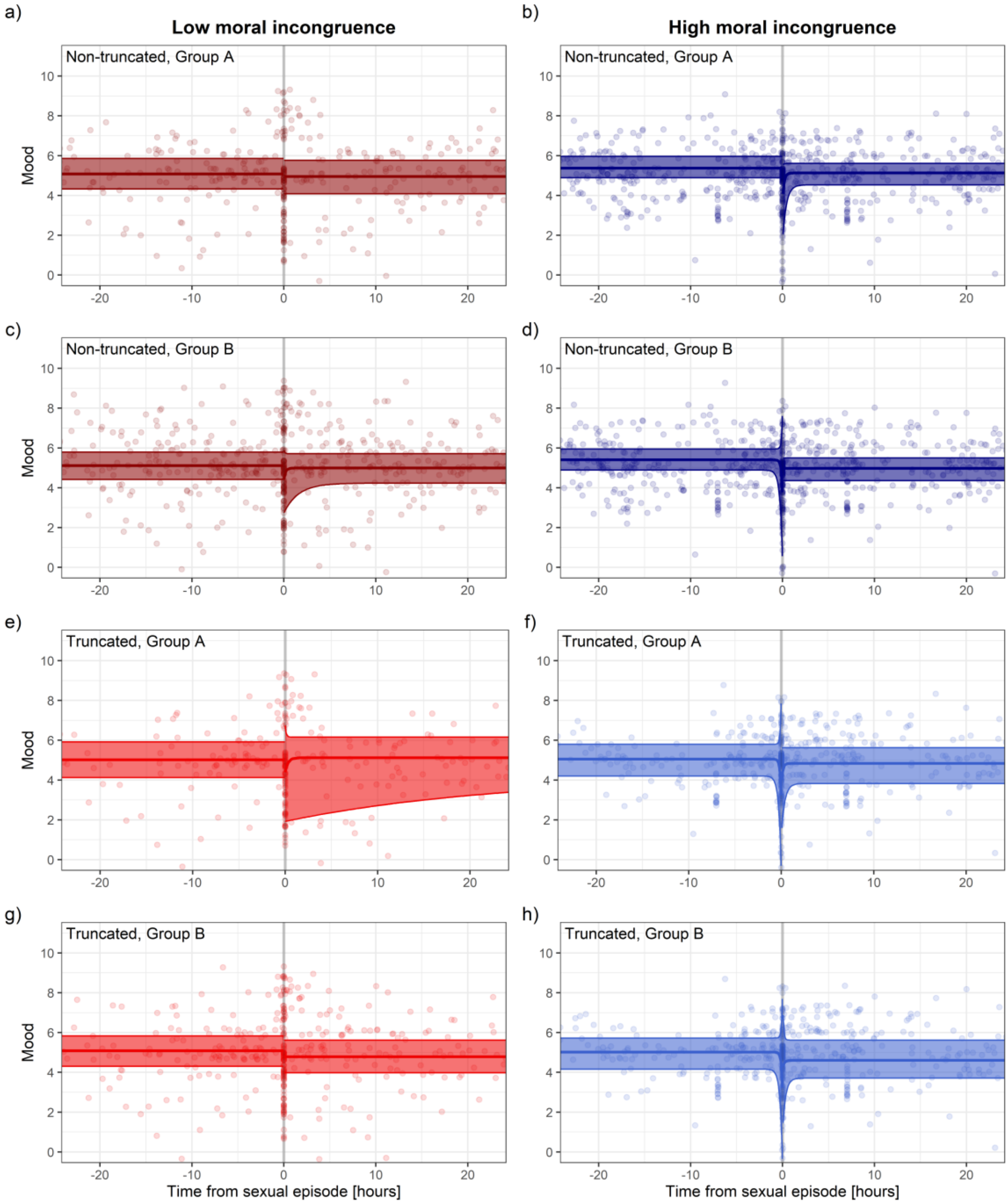


*Figure C7: Results from fitting hierarchical exponential models to 'mood' scores obtained pre- and post-sexual episodes, showing 24 hours before and after episodes.*

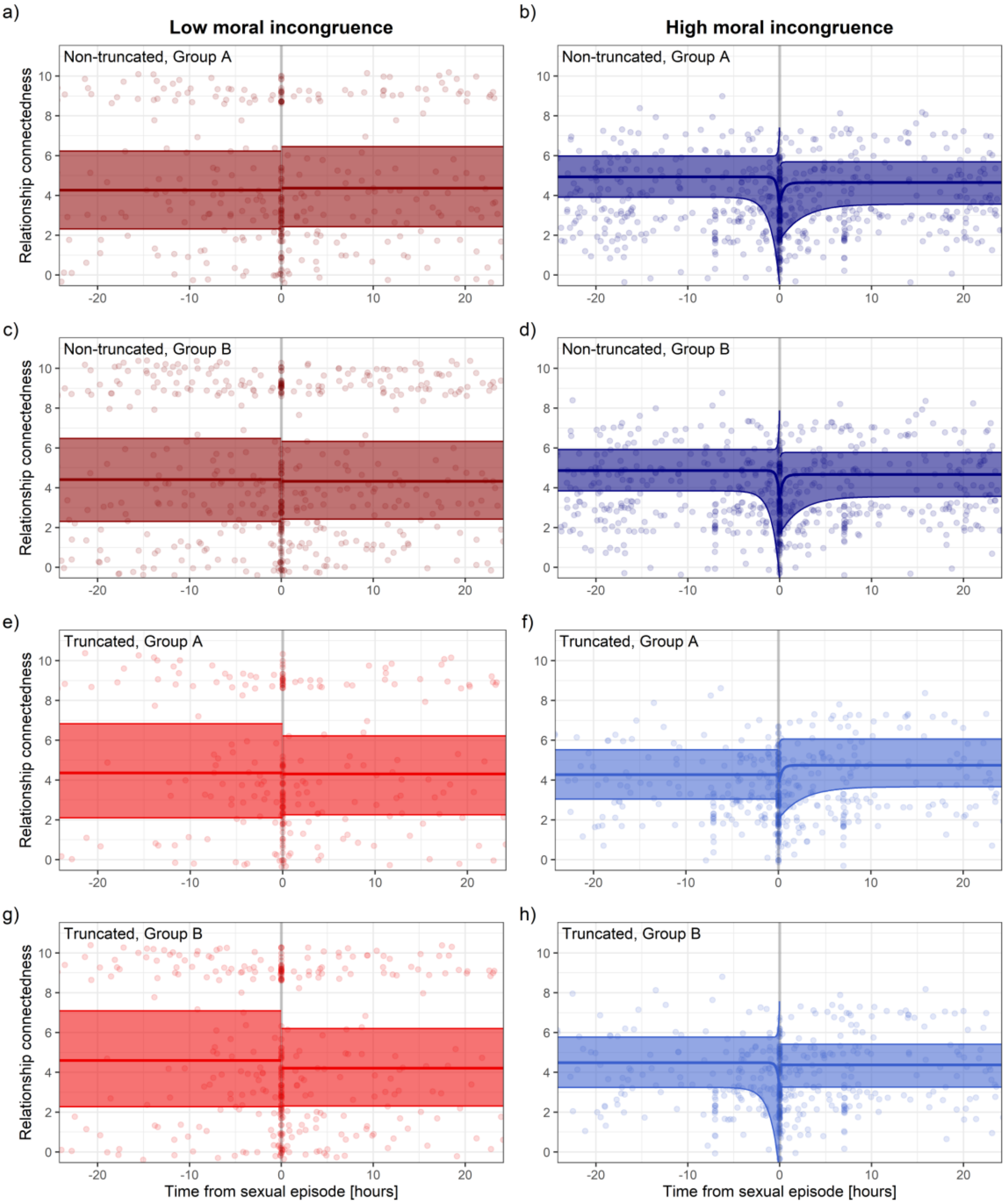


*Figure C8: Results from fitting hierarchical exponential models to 'relationship connectedness' scores obtained pre- and post-sexual episodes, showing 24 hours before and after episodes.*

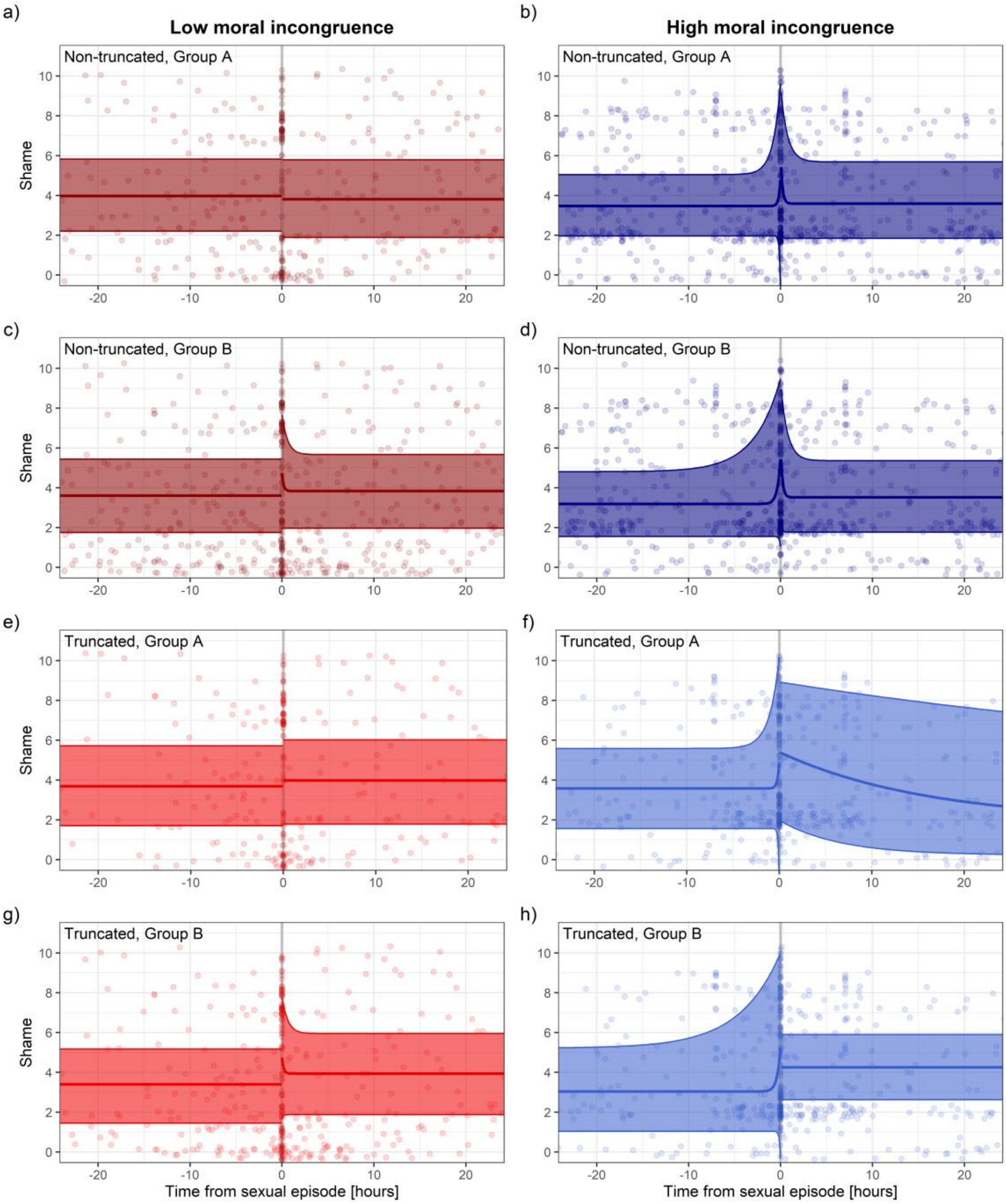


*Figure C9: Results from fitting hierarchical exponential models to 'shame' scores obtained pre- and post-sexual episodes, showing 24 hours before and after episodes.*