The Limit of an Investor's Capacity to Process Information

Thang Ngoc Nguyen

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Supervisors:

Professor Nhut (Nick) Hoang Nguyen
Associate Professor James G. Phillips
Professor Saten Kumar

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Abstract

Standard models of financial markets typically assume that investors can process available information efficiently and incorporate it into prices without substantial delay. However, research in behavioural finance and psychology suggests that individuals face limits in attention and cognitive processing capacity. Although prior studies document the consequences of limited investor attention in financial markets, less is known about how specific features of information environments jointly influence investors' decision quality and cognitive workload. This thesis addresses this gap by examining how information quantity, task complexity, irrelevant data, and time constraints affect financial decision-making.

The analysis is based on a controlled laboratory experiment in which participants perform stock valuation and trading tasks. Participants calculate the intrinsic value of firms using provided financial data and then decide whether to buy, hold, or sell the stock. Decision quality is measured using intrinsic value calculation accuracy and trading decision accuracy, while cognitive load is measured using self-reported mental effort.

The thesis consists of three studies. Study 1 examines the joint effects of information quantity and task complexity. The results show that both factors significantly reduce decision accuracy and that their interaction intensifies the decline in performance as cognitive demands increase. Study 2 introduces irrelevant financial information to examine whether non-diagnostic cues influence decision outcomes. The results indicate that irrelevant information reduces performance when the information environment is otherwise simple, although this effect weakens when overall information load is high, suggesting selective filtering of information. Study 3 examines the role of time constraints and shows that reducing time pressure significantly improves decision accuracy, particularly in tasks with high complexity and large information sets.

Overall, the findings provide experimental evidence that investor decision quality is strongly shaped by cognitive constraints. The thesis contributes to the literature on limited investor attention and cognitive load by demonstrating how multiple dimensions of information environments interact to influence financial decision-making. The results also have practical implications for financial disclosure design, suggesting that excessively complex or information-dense disclosures may hinder investors' ability to extract relevant signals.

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Chapter 1

Introduction

1.1 Background and motivation

Financial markets are often analysed as if investors can process available information efficiently and translate it into sound valuation and trading decisions. In that benchmark view, once relevant information becomes public, market participants assess it, update their expectations, and act accordingly. Yet this benchmark places heavy demands on the decision maker. It assumes not only that information is available, but also that investors can notice, interpret, compare, and integrate multiple signals accurately and within a useful period of time. In practice, that assumption may be too strong.

A large literature in finance suggests that investor attention is limited, selective, and costly (Merton, 1987; Sims, 2003; Peng, 2005; Peng & Xiong, 2006; Liu et al., 2023; Cronqvist et al., 2024). Investors do not process all available information with equal depth, nor do they always respond fully and immediately to every relevant cue. Empirical research shows, for example, that market reactions are weaker when attention is divided, such as when announcements are released at less salient times or when several firms compete simultaneously for investor focus (DellaVigna & Pollet, 2009; Hirshleifer et al., 2009; Liu et al., 2023; Xi et al., 2026). Related work in accounting and disclosure research reaches a similar conclusion. The usefulness of disclosures depends not only on informational content, but also on whether users are able to absorb and act on what is presented to them (deHaan et al., 2015; Koester et al., 2016; Blankespoor et al., 2020). In that sense, the efficiency of financial decision-making depends partly on the informational environment in which decisions are made, not merely on the availability of information.

This issue has become more important in modern financial environments. Investors are exposed to a vast and continuous flow of potentially relevant information, including earnings announcements, annual reports, analyst commentary, macroeconomic news, media coverage, and digital market data. Advances in disclosure, technology, and access to information have reduced some frictions but also created a more crowded decision environment. The challenge is no longer only about obtaining information. Increasingly, it is how to screen, prioritise, and use an abundance of it. More information may reduce uncertainty in principle, yet in practice it may also increase cognitive burden, compete for attention, and make accurate judgement harder rather than easier. This tension lies at the centre of the present thesis.

The problem is especially salient in financial tasks that require active calculation and structured reasoning. Investors are often not merely reacting to a headline or a single announcement. They must combine several indicators, translate those indicators into an estimate of intrinsic value, compare that estimate with a market price, and then convert the result into a discrete action such as buying, holding, or selling. These tasks require more than passive attention. They draw on working memory, sustained concentration, numerical processing, and coordination across multiple steps. When the informational environment becomes denser, more complex, more distracting, or more time constrained, decision quality may deteriorate even when all relevant information remains publicly available.

This thesis examines that possibility directly. It investigates how the structure of the information environment shapes investor judgement in a controlled stock-valuation and trading setting. More specifically, it studies the effects of information quantity, task complexity, irrelevant data, and time constraint on two forms of decision quality, intrinsic-value calculation accuracy and trading-decision accuracy, together with self-rated mental effort. In doing so, it brings together behavioural finance and cognitive psychology in order to provide a more explicit account of why investors may struggle in information-rich environments.

1.2 Research problem and gap in the literature

The finance literature already provides strong reasons to believe that cognitive constraints matter. Limited attention has been linked to underreaction to earnings news, distraction effects, and variation in the usefulness of disclosures across informational settings (DellaVigna & Pollet, 2009; Hirshleifer et al., 2009; deHaan et al., 2015). Rational inattention models formalise the same broad idea by treating information processing as scarce and costly. In these models, decision makers do not absorb all signals with equal precision. Instead, they allocate limited processing capacity selectively across available information (Sims, 2003; Peng, 2005; Peng & Xiong, 2006). This literature has been highly influential, but much of it remains indirect. It often infers cognitive limits from market-level outcomes rather than observing, at the individual level, how investors perform when the demands of a financial task become cognitively heavy.

That leaves an important gap. Existing work shows that attentional constraints matter, but often says less about the specific task conditions under which those constraints begin to impair judgement. In particular, there has been relatively little direct evidence on how several distinct sources of processing demand combine within the same financial decision environment. A person may encounter a large amount of information, but that is not the same as facing a highly complex task. A task may be demanding even when the information set is modest, if it requires more calculations, more coordination across steps, or more integration across interdependent cues. Irrelevant information introduces an additional challenge because it may occupy attention without contributing meaningfully to the actual decision. Time constraints add another layer, because the same information environment may be manageable when participants have sufficient time, yet much harder when the decision must be made quickly. These pressures are related but not identical.

The information-overload and accounting literatures come closer to these questions, especially in their treatment of load, presentation format, and judgement quality (Bettman & Kakkar, 1977; Iselin, 1988; Vessey, 1991). Even so, a persistent ambiguity remains. In many studies, higher information load is created by adding more information to the same decision problem. This makes it difficult to distinguish the burden of processing from the possible value of the additional information. If more information is also more useful, then poorer performance cannot be attributed cleanly to overload alone. The present thesis addresses this problem by following Iselin (1988) and Shields (1983) in defining higher information quantity as an increase in the amount of structurally equivalent information that must be processed to reach the same type of decision. Within a given complexity level, the valuation algorithm, information types, and response format remain constant. Only the number of like cues changes. This design removes the usual information-value confound and allows the analysis to focus more clearly on processing burden itself.

A second gap concerns the connection between finance and cognitive psychology. Finance research often refers to attention, distraction, or overload, but these ideas are not always tied to a detailed theory of cognitive capacity. Psychology offers a useful framework for doing so. Working-memory research suggests that people can maintain and manipulate only a limited amount of information at one time, especially when several operations must be coordinated simultaneously (Baddeley & Hitch, 1974). Cognitive Load Theory extends this insight by distinguishing between demands inherent to the task and those that consume resources without directly contributing to task completion (Sweller, 1988; Paas et al., 2003). From this perspective, performance falls not simply because information is present in large volume, but because the total demands of the task exceed the decision maker's processing capacity.

This theoretical bridge matters because it sharpens our understanding of the mechanism underlying limited attention. It suggests that investor errors in dense and demanding information environments may arise not merely because investors are inattentive in a broad sense, but because the decision environment places excessive pressure on working memory and cognitive processing. The present thesis therefore treats limited attention as part of a broader capacity-constraint problem. It asks when features of a financial task push participants toward the limits of processing capacity, and whether this is reflected in both lower objective accuracy and higher subjective mental effort.

1.3 Theoretical framing

1.3.1 Limited attention, working memory, and cognitive load

The central premise of this thesis is that investor judgement is constrained by scarce cognitive resources. In finance, that idea appears in limited-attention and rational-inattention frameworks. In psychology, it appears in theories of working memory and cognitive load. These traditions use different language, but they converge on a similar point. Decision quality depends partly on whether the demands of the task remain within the decision maker's available processing capacity.

Working memory is especially relevant here because the financial tasks examined in this thesis require temporary storage and active manipulation rather than simple recognition. Participants must retain several cues, perform calculations, compare computed values with hypothetical market prices, and then map the result onto a buy, hold, or sell decision. These operations place demands on both storage and processing. As those demands increase, the task becomes more vulnerable to omission, mis-sequencing, simplification, and error (Baddeley & Hitch, 1974). Cognitive Load Theory provides a useful way to organise these pressures. Intrinsic load refers to the demands inherent in the material itself, especially the number of interacting elements that must be processed together. Extraneous load refers to demands created by the presentation or environment that consume resources without directly supporting performance (Sweller, 1988; Paas et al., 2003).

This distinction is central to the present thesis. Information quantity and task complexity are treated mainly as sources of intrinsic demand. Irrelevant data is treated as a source of extraneous demand. Time constraint does not add informational content by itself, but it limits the opportunity to manage both kinds of demand and may therefore intensify their effects on performance. This framework makes it possible to interpret changes in decision quality and self-rated mental effort not simply as isolated empirical patterns, but as manifestations of how different task features place pressure on limited working-memory resources.

1.3.2 Information quantity and task complexity

Information quantity matters because more cues require more screening, retention, and integration. Yet the effect of additional information is not straightforward. Under some conditions, more information should improve judgement by reducing uncertainty. Under other conditions, especially when the task is computational and time sensitive, additional information may impose a burden that outweighs its potential benefit (Iselin, 1988; Roetzel, 2019). The critical issue is therefore not only whether information is available, but whether it can be used effectively. In the present thesis, higher information quantity means that participants must process more companies of the same type using the same task logic. This allows the thesis to isolate more clearly the burden of processing more information, rather than the value of receiving different information.

Task complexity is closely related, but conceptually distinct. Information quantity refers primarily to how much information is available to the decision maker. Task complexity refers to how difficult that information is to organise, interpret, and integrate into a judgement. A task may therefore become more demanding because it contains more cues, because the relationships among those cues are more intricate, or because both conditions apply. Following Wood's (1986) framework, the present thesis treats complexity as having two main aspects. Component complexity refers to the number of cues and acts required to perform the task. Coordinative complexity refers to the extent to which later steps depend on earlier steps and the degree of coordination needed across acts. This distinction is important because many financial decisions are not simple cue-recognition tasks. Investors often need to combine several indicators, understand how those indicators relate to one another, and translate that interpretation into a valuation or trading judgement.

A key implication follows from this distinction. Information quantity and task complexity may not operate independently. A larger information set may remain manageable when the task itself is simple, yet the same increase in quantity may become much more harmful when the task also requires more coordination, more steps, and more integration across cues. Cognitive Load Theory suggests that such conditions may generate more than an additive increase in demand, pushing decision makers closer to an overload region where additional effort can no longer fully offset processing difficulty. This possibility is central to the empirical design of Study 1.

1.3.3 Irrelevant data and time constraint

Real financial decision environments are rarely perfectly curated. Relevant cues often appear alongside details that are salient or superficially informative but not actually diagnostic for the task at hand. In this thesis, irrelevant data refers to information that is clearly non-diagnostic for the valuation problem. The expectation is not necessarily that such information will always produce large performance losses. Rather, it may absorb scarce attention, increase perceived effort, and interfere with the processing of relevant information in some settings. Within a cognitive-load framework, this is best understood as a form of extraneous demand.

The literature on the dilution effect and on seductive details provides the logic for this expectation. When diagnostic and non-diagnostic information are presented together, individuals do not always discount the irrelevant material fully. Instead, they may spread attention too broadly across available cues, weakening the role of the most useful information (Nisbett et al., 1981; Harp & Mayer, 1998; Rey, 2012). Recent work continues to support the idea that irrelevant or weakly diagnostic material can impair decision quality by diverting attention and increasing non-productive processing demands. In the seductive-details literature, irrelevant but interesting material has been shown to increase extraneous cognitive load and impair learning performance (Wesenberg et al., 2024; 2025). In auditing, irrelevant information can likewise reduce skeptical judgment (Giordano & Victoravich, 2025). Related finance evidence shows that irrelevant managerial responses can increase analyst forecast errors, while disclosure features that raise cognitive burden can impede the processing of value-relevant information (Hao et al., 2025). More broadly, investors also appear to pay limited attention to less salient details in financial statements, suggesting that longer, denser, or less clearly organised disclosures may burden users even when the additional material is not directly useful (Cronqvist et al., 2024).

Time adds a further complication. A time constraint is an objective feature of the task, whereas time pressure refers to the subjective experience that such a constraint may generate. This distinction matters because the same deadline may feel manageable in one setting and highly restrictive in another. Research suggests that tighter deadlines change both how much information people process and how they process it. Under greater urgency, decision makers tend to search less extensively, filter more aggressively, and rely more on simplifying strategies (Edland & Svenson, 1993; Payne et al., 1996; Eppler & Mengis, 2004; Roetzel, 2019). In finance-related settings, this may weaken valuation accuracy and reduce the quality of the final trading decision.

Recent evidence also suggests that time effects are often conditional rather than uniform. Tight deadlines do not necessarily harm every outcome in every setting, and expertise may offset some of the cost. Even so, the broader pattern suggests that time becomes most consequential when the task itself is already demanding (Cao et al., 2022). This is important for the present thesis. Time is not treated here as merely a background control variable. Instead, it is examined as a factor that may moderate how strongly information quantity and task complexity translate into lower performance and higher effort.

1.4 Research aim, objectives, and questions

Against this background, the overall aim of this thesis is to explain how features of the information environment shape the quality of investor decisions and perceived mental effort in a controlled financial decision-making setting.

To achieve that aim, the thesis pursues four related objectives. First, it examines whether greater information quantity reduces performance and increases mental effort. Second, it tests whether higher task complexity has similar effects, and whether the two pressures reinforce one another. Third, it investigates whether clearly irrelevant information imposes an additional burden beyond the core demands of the task. Fourth, it examines whether a more relaxed time condition alters these relationships.

These objectives are organised around three research questions. The first asks how information quantity and task complexity affect intrinsic-value calculation accuracy, trading-decision accuracy, and self-rated mental effort. The second asks whether the addition of irrelevant data changes those outcomes, either on average or in interaction with the wider informational setting. The third asks whether a more relaxed time condition weakens the adverse effects of information quantity and task complexity, and whether any benefit appears in both objective performance and subjective effort.

1.5 Research design and empirical setting

The thesis addresses these questions through a laboratory stock-trading experiment in which participants calculate the intrinsic value of stocks and make trading decisions under systematically varied task conditions. This design is useful because it permits close control over the informational features of the decision environment while preserving a recognisably financial task structure.

Participants calculate intrinsic values using well-known valuation models, including the price-to-earnings ratio, the Gordon growth model, and the Capital Asset Pricing Model. They then compare their calculated values with hypothetical market prices and choose whether to buy, hold, or sell the stock. This structure allows the thesis to distinguish between two related but separate forms of decision quality, the accuracy of the underlying intrinsic-value calculation and the accuracy of the trading decision based on that calculation. Financial information is presented in tabular form, which fits the symbolic and analytical nature of the task and is consistent with cognitive-fit arguments about matching representation format to problem type (Bettman & Kakkar, 1977; DeSanctis, 1984; Vessey, 1991).

The research consists of three related studies and nine experimental conditions. In all studies, task complexity varies within participants, so each participant completes five question sets that correspond to the five levels of overall task complexity. Information quantity varies between participants across three levels: low, medium, and high. In the low information-quantity condition, each task includes two companies. In the medium and high information-quantity conditions, each task includes four and six companies, respectively. Study 2 introduces irrelevant data, namely number of employees and research and development expenditure, while otherwise matching the corresponding clean-information conditions. Study 3 varies the time constraint by comparing a tighter three-minute condition with a more relaxed five-minute condition. Participants also report their mental effort after each task using Paas's (1992) nine-point mental-effort scale, which provides a repeated subjective indicator of cognitive burden.

A further strength of the design lies in the way information quantity is defined. Consistent with Iselin (1988) and Shields (1983), information quantity is treated as a change in the amount of structurally equivalent information that must be processed to reach the same type of decision. The lower information-quantity condition is a subset of the higher information-quantity conditions, and the higher-load task uses the same valuation algorithm, the same information types, and the same response format as the lower-load task. The higher-load task simply adds more companies of the same type. This design helps remove the usual information-value confound and makes it more plausible that any systematic deterioration in performance reflects the burden of processing more information.

The participant pool consists primarily of senior undergraduate students in finance-related disciplines from three Vietnamese universities. All had already completed coursework covering asset pricing and stock valuation, including the valuation models used in the experiment. This background is important because the design does not test whether participants have seen these concepts before. Rather, it tests how well they process structured financial information under different task demands once the basic domain knowledge is already in place. This is consistent with the role of student samples in experimental economics, accounting, and finance when the aim is to study general behavioural mechanisms rather than institution-specific professional expertise (Cueva et al., 2019; Frydman et al., 2014; Kirchler et al., 2018). The thesis also includes a professional replication in Study 3 under the high-information condition in order to examine external validity more directly.

1.6 Overview of the three studies

Study 1 establishes the central pattern of the thesis. It examines how information quantity and task complexity jointly shape performance and mental effort. The results show a clear gradient. As information quantity rises and the task becomes more complex, intrinsic-value calculation accuracy and trading-decision accuracy both decline, while perceived mental effort increases. More importantly, the two objective performance effects are not merely additive. The negative effect of complexity becomes steeper as information quantity rises, and the negative effect of information quantity becomes larger as complexity increases. This compounding pattern is evident in both intrinsic-value calculations and trading decisions. By contrast, self-rated mental effort rises with both factors but shows little evidence of a strong interaction, suggesting a largely additive increase in experienced burden. These findings indicate that both the amount of information to be processed and its difficulty are costly, and that their joint effect is especially damaging to decision quality.

Study 2 extends this logic by considering a more realistic feature of financial decision environments, namely the presence of irrelevant information. Investors rarely face perfectly filtered sets of diagnostic cues. Relevant information is often mixed with other details that may attract attention without helping the task itself. Study 2 therefore adds clearly non-diagnostic firm cues while leaving the underlying valuation problem unchanged. The results suggest that irrelevant data matters, but not in the same way as the core load variables. Task complexity and information quantity remain the dominant drivers of lower accuracy and higher effort. Once these are accounted for, the average impact of irrelevant information on objective accuracy is modest and generally statistically weak. The clearer pattern appears in self-rated mental effort, which rises when irrelevant cues are present. There is also some indication that the irrelevance penalty is greater in simpler, lower-information environments than in already dense ones. This pattern is consistent with the idea that irrelevant cues behave as a mild source of extraneous load. They are more disruptive when some spare attentional capacity remains available, but become easier to ignore once participants are already operating close to their capacity limit.

Study 3 then considers whether the effects documented in Study 1 depend on the amount of time available to complete the task. Participants face the same basic information-quantity and task-complexity structure, but under two timing regimes, three minutes or five minutes per question. The results suggest that time operates mainly as a moderator rather than as a simple average shift. Under the tighter regime, both intrinsic-value accuracy and trading accuracy decline sharply as complexity and information quantity rise, and the negative interaction between these two factors remains evident. When participants are given more time, the main time effect is not the most informative feature. Instead, the interaction terms show that additional time matters most where processing demands are highest. For intrinsic-value accuracy, the longer time window substantially flattens the complexity gradient. For trading accuracy, the strongest moderation appears for information quantity, with the penalty from added information becoming much smaller under the more relaxed time condition. The evidence for a direct average effect on self-rated mental effort is weaker, which suggests that time pressure may lower performance partly by inducing earlier closure and more selective cue use rather than by producing a robust increase in experienced workload. Study 3 therefore supports the view that time constraint primarily changes the effectiveness of processing under high demand rather than simply making tasks feel harder in every respect.

Study 3 also includes a professional replication under high information load. This extension provides a useful external-validity check. The evidence suggests that extra time improves professionals' accuracy as well, although the shape of the effect differs somewhat from the student sample. Among professionals, the longer time window appears to lift performance more broadly across complexity levels, rather than mainly altering the marginal slope of task demands. This difference is consistent with the idea that expertise may allow time slack to be used for verification and error checking. At the same time, under tight time constraints, professionals and students display broadly similar complexity penalties, which supports the external validity of the student-based findings in demanding high-information environments.

Taken together, the three studies point to a coherent pattern. Information quantity and task complexity exert strong and direct pressure on decision quality. Irrelevant data appears to increase perceived effort more reliably than it lowers accuracy. Time, in turn, alters how damaging the other pressures become. This suggests that information burden is not best understood as a single undifferentiated condition. Different sources of burden appear to operate through somewhat different channels and have different implications for performance and experience.

1.7 Contributions of the thesis

This thesis makes several contributions.

First, this thesis contributes to behavioural finance by providing direct individual-level evidence on how cognitive constraints shape investor decision quality. Existing finance research often infers limited attention from market-level outcomes rather than observing how investors perform on demanding financial tasks. The present thesis addresses that gap by examining how variations in information quantity, task complexity, irrelevant data, and time constraint affect intrinsic-value calculation accuracy, trading-decision accuracy, and self-rated mental effort in a controlled experimental setting. This helps identify a more specific behavioural channel through which limited processing capacity may influence financial judgement.

Second, it contributes to the information-overload literature by separating information quantity from information value. Because higher-load conditions require participants to process more of the same type of information in a structurally equivalent task, the results can be interpreted more clearly as evidence on processing burden rather than on changes in informational usefulness.

Third, the thesis contributes to the dialogue between finance and cognitive psychology. It shows that concepts such as working memory, intrinsic load, and extraneous load help explain why investor judgement may deteriorate when financial tasks become dense, complex, distracting, or rushed. This gives the thesis a clearer mechanism than a simple appeal to distraction alone.

Fourth, the thesis offers a more differentiated account of informational burden. More information, greater complexity, irrelevant cues, and tighter time constraints all matter, but they do not matter in exactly the same way. Information quantity and task complexity directly weaken accuracy and raise effort. Irrelevant cues raise effort more consistently than they lower performance. Time mainly moderates the harm caused by the other burdens. This distinction is important because it suggests that overload should not be treated as a single broad label. It is better understood as a family of related but analytically distinct pressures.

Finally, the thesis has practical relevance for disclosure design, investor education, and investor-facing decision environments. If judgement worsens when information becomes harder to process, then better decisions may require more than simply providing more data. Clearer organisation, reduced irrelevant detail, and more realistic decision time may also matter. In that sense, the thesis speaks not only to academic debates about limited attention, but also to broader questions of how financial information can be structured so that it is actually usable.

1.8 Structure of the thesis

The remainder of the thesis is organised as follows.

Chapter 2 reviews the literature on limited investor attention, working memory, cognitive load, information overload, task complexity, irrelevant information, and time pressure. It develops the theoretical framework and derives the study hypotheses.

Chapter 3 explains the methodology, including the experimental design, task construction, measurement choices, participant recruitment, and empirical strategy.

Chapter 4 reports Study 1 and examines the joint effects of information quantity and task complexity on intrinsic-value calculation accuracy, trading-decision accuracy, and self-rated mental effort.

Chapter 5 reports Study 2 and evaluates whether the addition of irrelevant data changes decision quality and perceived effort beyond the core load effects identified in Study 1.

Chapter 6 reports Study 3 and tests whether a more relaxed time condition alters the relationship between information quantity, task complexity, performance, and mental effort. It also includes professional replication and external validity analysis.

The final chapter draws the findings together, discusses their implications for behavioural finance and cognitively grounded accounts of investor judgement, considers the limitations of the thesis, and outlines directions for future research.

Chapter 2

Literature Review

2.1 Limited investor attention

Traditional finance is largely built on the assumption that investors process available information rationally and that prices adjust efficiently to public news. In that benchmark view, once relevant information is disclosed, market participants evaluate it and incorporate it into valuations through their trading decisions. This framework has been highly influential, but it also rests on a demanding behavioural assumption. It assumes that investors can notice, interpret, and integrate a large amount of information with relatively little friction. The literature on limited investor attention tempers that assumption by arguing that attention is scarce, selective, and costly. Investors may wish to process all value-relevant information, but in practice they face finite cognitive resources and cannot attend to everything at once. As a result, market outcomes depend not only on what information is available, but also on which signals attract attention, when they arrive, and what competing demands are present at the same time.

This idea matters because attention is a necessary precondition for information use. Before information can influence beliefs, valuations, or trading decisions, it must first be noticed and processed. If attention is limited, then even public and relevant information may be only partially incorporated into judgement, at least in the short run. Limited attention therefore refers to more than occasional distraction. It reflects a broader constraint on how individuals allocate scarce mental resources across competing stimuli. In financial settings, that constraint is especially important because investors often face dense, fast-moving, and numerically complex information environments in which several signals may compete for attention simultaneously.

The theoretical literature converges on this general point, although it formalises the mechanism in different ways. Merton (1987) argues that investors face costs of acquiring and processing information, which means that incomplete awareness is a normal feature of financial markets rather than an anomaly. Odean (1999) develops a related insight by suggesting that investors are more likely to purchase attention-grabbing stocks because they do not screen the full universe of available securities from scratch. Rational inattention models deepen this argument by treating information-processing ability as a scarce resource that must be allocated selectively across signals. Sims (2003) shows that bounded processing capacity can be analysed as an optimization problem, while Peng (2005) and Peng and Xiong (2006) apply similar logic to financial markets and show how limited capacity can shift attention away from firm-specific information and toward broader market or sector cues. In these models, bounded attention does not simply imply irrationality. Rather, it implies constrained optimization under finite cognitive bandwidth.

More recent work extends this logic to sophisticated market participants. Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) show that even professional fund managers vary the type of information they process depending on market conditions and the expected value of that information. Lu (2022) similarly argues that disclosure complexity and processing costs can limit the extent to which users extract information from financial reports. These studies are important because they suggest that attentional limits are not confined to inexperienced retail investors. Even highly trained decision-makers appear constrained by the fact that mental resources are finite and must be allocated selectively.

The empirical finance literature broadly supports these theoretical predictions. A recurring finding is that market responses weaken when attention is divided. DellaVigna and Pollet (2009), for example, show that earnings announcements released on Fridays receive weaker immediate reactions, which is consistent with lower investor attention at that time. Hirshleifer, Lim, and Teoh (2009) similarly find that when many firms announce earnings on the same day, the market underreacts more strongly, which suggests that attention is stretched across competing disclosures. Recent evidence continues to show that market reactions are weaker when investor attention is divided or when disclosure arrives in lower-attention windows. For example, simultaneous overnight announcements by multiple firms dilute the price-discovery benefits of announcement releases, while downward analyst forecast revisions disclosed during weekday non-trading hours attract less attention and elicit weaker price reactions (Liu et al., 2023; Xi et al., 2026). These findings are useful because they show that the market's response depends not only on the informational content of an announcement, but also on the attentional environment in which that announcement is received.

Related studies indicate that these effects are not confined to announcement returns. Corwin and Coughenour (2008) show that market makers allocate attention across the stocks they handle, and that this allocation affects trading quality and liquidity. Chakrabarty and Moulton (2012) provide related evidence that attention constraints shape trading outcomes in market settings. More broadly, this literature suggests that when investor attention is occupied elsewhere, pricing becomes less responsive, adjustments become slower, and informational efficiency is weaker. The point is not that investors ignore relevant information entirely. Rather, information may be incorporated more slowly, less fully, or less consistently because attention must be divided across multiple tasks and signals.

A similar pattern appears in the analyst and disclosure literature. Analysts operate in an environment where attention is likely to be constrained because they monitor many firms, process repeated disclosures, and often update expectations under time pressure. Prior research suggests that when users face competing informational demands, their ability to interpret and respond to corporate news may deteriorate. Hirst and Hopkins (1998) show that presentation format affects how effectively users extract information from financial reports. Bourveau, Lou, and Wang (2024) and Driskill et al. (2020) provide more direct evidence that attention constraints can affect analyst judgement and forecast-related outcomes. Blankespoor, deHaan, and Marinovic (2020) similarly review a broad disclosure literature and conclude that limited attention and processing costs materially shape how market participants interpret corporate communications. Taken together, this work suggests that attentional constraints operate not only through investor distraction in a narrow sense, but also through the way information is formatted, timed, and embedded within broader disclosure environments.

Another important implication is that firms may respond strategically to predictable variation in investor attention. If managers understand that attention fluctuates across time and context, they may have incentives to release information when scrutiny is weaker or when other news is likely to crowd out careful processing. Evidence on Friday announcements, after-hours disclosures, and strategically timed news is broadly consistent with this possibility. DellaVigna and Pollet (2009) show that firms can benefit from releasing earnings news at times of lower attention. deHaan, Madsen, and Piotroski (2015) and Koester, Lim, and Tucker (2016) provide related evidence that managerial disclosure choices may respond to the attentional state of the market. This is important because it suggests that limited attention does not merely affect passive market reception. It can also shape managers' behaviour and alter the structure of the information environment itself.

The governance literature points in the same direction. Kempf, Manconi, and Spalt (2017) show that distracted shareholders monitor firms less effectively, which can make it easier for managers to undertake value-destroying actions. This broadens the significance of limited attention beyond short-run mispricing. Attentional constraints may also affect governance quality, the effectiveness of shareholder oversight, and the extent to which firms are held accountable by external market participants. In that sense, limited attention has implications at several levels. It can shape what investors notice, how deeply they process it, how quickly prices adjust, and how firms choose to communicate with the market.

It is also useful to distinguish limited attention from information overload, because the two concepts are related but not identical. Limited attention refers to the finite capacity of decision-makers to allocate mental resources across multiple stimuli. Information overload refers more specifically to a state in which the volume, complexity, or diversity of information exceeds the decision-maker's capacity to process it effectively. Put differently, limited attention is a general constraint, whereas information overload is one important condition under which that constraint becomes especially binding. This distinction matters for the present thesis. Investors may experience attentional limits even in relatively modest decision environments, but those limits are likely to become more consequential when information quantity increases, when task structure becomes more complex, when some cues are irrelevant, or when available time is restricted. The literature on limited attention therefore provides the broader conceptual foundation, while the literature on overload, complexity, irrelevance, and time pressure helps specify the conditions under which performance is most likely to deteriorate.

The relevance of limited attention is especially strong in modern disclosure environments. Contemporary financial markets expose investors to a near-continuous stream of earnings announcements, management guidance, annual reports, analyst commentary, media coverage, and online discussion. At the same time, disclosure documents themselves have often become longer and more complex. This means that investors are not simply processing more information than in earlier periods. They are also processing information that arrives more quickly, through more channels, and often in more elaborate forms. Under these conditions, the challenge is not merely to obtain information. It is to identify which information is diagnostic, to filter out less useful cues, and to do so quickly enough for the information to retain decision value. Limited attention is therefore not a peripheral issue in modern finance. It is central to understanding how investors cope with increasingly demanding informational environments.

Despite the considerable progress of this literature, an important gap remains. Much of the finance evidence identifies limited attention indirectly through market-level outcomes such as announcement returns, trading behaviour, forecast revisions, or disclosure timing. These studies are highly informative, but they do not directly observe the moment at which an individual decision-maker becomes cognitively stretched or begins to simplify the processing of financial information. As a result, the underlying decision environment through which attention constraints affect judgement remains less clearly understood. In particular, less is known about how investor performance changes when individuals must process multiple numeric cues, distinguish relevant from irrelevant information, and make valuation and trading decisions under explicit time limits.

This gap is important because real financial decisions often require more than reacting to a headline or noticing a single announcement. Investors frequently need to integrate several firm characteristics, interpret their joint implications, and translate those assessments into a concrete judgement. In such settings, limited attention is likely to interact with other task features rather than operate in isolation. A decision-maker may be able to process a modest amount of relatively simple information when time is ample, yet perform much less effectively once the informational environment becomes denser, the relationships among cues become less straightforward, or the available time becomes more restrictive. The broader limited-attention literature strongly implies such a mechanism, but it rarely tests it directly in a controlled individual-decision setting.

2.1.1 Why do attentional constraints of investors affect stock prices?

The literature reviewed so far suggests that investors are subject to attentional constraints. An additional question, however, is why these individual-level limits should affect stock prices if more sophisticated traders can, in principle, correct any resulting mispricing. Behavioural finance addresses this issue through the idea of limited arbitrage. If fully rational investors have finite risk-bearing capacity, their beliefs do not immediately determine prices. Instead, prices reflect a weighted average of investor beliefs, where influence depends on factors such as market participation, risk tolerance, and trading intensity. In principle, wealth may gradually shift from less rational to more rational investors, thereby weakening the influence of inattentive traders over time. In practice, however, this process is often slow and incomplete. Prices are noisy, learning is imperfect, and some traders may not become more rational with experience, which limits the speed with which market influence shifts toward more sophisticated traders (Korniotis & Kumar, 2011; Spaniol & Bayen, 2005; Hirshleifer et al., 2009).

This point is reinforced by evidence suggesting that institutional investors cannot simply be treated as a complete corrective force. Although institutions are often more sophisticated than retail investors, their trading is not always fully rational or fully informative. Prior work suggests that institutional behaviour may itself reflect overreaction, underreaction, herding, or other forms of imperfect processing (Carpentier & Suret, 2021; Wulfmeyer, 2016; Wang et al., 2024). Related studies further suggest that irrational institutional trading can contribute to post-earnings announcement drift or broader misvaluation (Frazzini, 2006; Zeng, 2016; Chou et al., 2021). These findings weaken the view that arbitrage by sophisticated traders will necessarily eliminate the effects of limited attention on prices.

A further reason attentional constraints can matter for pricing is that investors do not always compensate optimally for the information they have failed to process. In theory, an investor who recognises that some relevant signal has been overlooked could adjust by trading less or by placing less weight on his or her own valuation. In practice, however, such compensation is difficult to achieve. It is often hard to determine which signals are most important before they have been processed in some depth, and the same cognitive limitations that cause neglect may also make it difficult to correct for that neglect afterwards. Empirical evidence shows that investors trade actively even when they do not possess superior valuations, often with poor timing and weak diversification (Barber & Odean, 2000). More recent evidence suggests that platform design can intensify this problem by encouraging trading in attention-grabbing stocks rather than in response to fundamentals (Barber et al., 2022). Experimental evidence in psychology points in the same direction, showing that people do not fully compensate for missing or incomplete information even when such incompleteness is visible (Tversky & Kahneman, 1981; Brenner et al., 1996).

Finally, inattentive or imperfectly informed investors need not withdraw from the market. Traditional models of information and securities markets imply that even less-informed traders may still trade on the basis of their own beliefs, especially when prices aggregate information imperfectly because of noise trading or liquidity demand (Grossman & Stiglitz, 1976). Hirshleifer et al. (2009) make a similar point in arguing that trading can remain reasonable even when some information is being overlooked. This matters because it shows that limited attention is not only an individual-level cognitive issue. It can also have market-level consequences. At the same time, the finance literature mainly explains why these effects can persist, rather than what cognitive mechanism produces them.

2.2 Limited cognitive capacity in psychology

The finance literature therefore establishes why limited attention can matter for market outcomes. If inattentive or imperfectly attentive investors influence trading, and if arbitrage does not fully eliminate those effects, then attentional constraints can affect prices as well as individual judgement. The next step is to explain the cognitive mechanism underlying that constraint. For that reason, the review now turns to psychology and working memory, which provide the theoretical foundation for understanding why financial information processing is limited in the first place.

2.2.1 Working memory as the basis of limited cognitive processing

Working memory plays a central role in this explanation. It is commonly defined as a limited-capacity system responsible for the temporary storage and active manipulation of information needed for ongoing thought and action (Atkinson & Shiffrin, 1968; Baddeley & Hitch, 1974). Because this system can handle only a limited amount of material at once, performance tends to decline when tasks require individuals to coordinate too many cues, steps, or mental operations simultaneously. This insight is especially relevant to financial decision-making, where investors often need to process several numerical indicators, evaluate their joint meaning, and convert that assessment into a valuation or trading decision.

On this view, limited attention in financial settings is not merely a descriptive behavioural pattern. It is rooted in a more fundamental cognitive constraint on how much information can be processed accurately and coherently at any given moment. Psychological research has long shown that attention is limited. Classic studies such as the Stroop task demonstrate that individuals struggle when required to suppress one stream of information while responding to another, suggesting that selective control is imperfect and resource-dependent (Stroop, 1935). Research on dichotic listening reaches a similar conclusion by showing that when two auditory streams compete for processing, people can generally attend closely to only one while the unattended channel receives much less semantic analysis (Broadbent, 1958; Cherry, 1953; Moray, 1959). More broadly, dual-task research suggests that performance often deteriorates when individuals must carry out two attention-demanding tasks at the same time. Taken together, these findings support the broader view that human cognitive processing is selective and capacity-limited rather than unlimited.

The literature on working-memory capacity deepens this point. Since the early formulation of working memory by Miller, Galanter, and Pribram (1960), and its later development in modern cognitive psychology, working memory has become a central concept in explaining reasoning, learning, problem-solving, and other mentally demanding activities (Baddeley A., 2007; Camos & Barrouillet, 2018; Engle et al., 2005; Hambrick et al., 2021; Logie et al., 2021; Mashburn et al., 2021). A particularly important feature of this system is its limited capacity. Early discussions of short-term memory often referred to Miller's estimate of seven plus or minus two chunks (Miller G., 1956), but later work has argued that the effective functional limit is often smaller once rehearsal and chunking are controlled. Research by Luck and Vogel and by Cowan, among others, suggests that active processing capacity may often be closer to about four chunks (Cowan N., 2001; Luck & Vogel, 1997). The precise number is less important here than the broader implication. Human cognition cannot maintain and process an unlimited number of elements at the same time.

This distinction is especially important for the present thesis because the issue is not only how much information investors can store briefly, but also how much they can process accurately while solving financially relevant problems. Since its inception, working memory has been understood as involving both maintenance and processing (Atkinson & Shiffrin, 1968; Baddeley & Hitch, 1974). The relationship between these two functions remains debated. Some researchers argue that storage and processing depend on distinct systems or resource pools, whereas others argue that they draw on a shared limited-capacity system (Baddeley A. , 1986; Baddeley & Logie, 1999; Barrouillet & Camos, 2015; 2021; Chen & Cowan, 2009; Cowan et al., 2021). The present thesis does not attempt to resolve that broader theoretical dispute. Instead, it focuses on the processing demands placed on working memory when individuals must integrate multiple numerical cues and use them to reach a financial judgement.

2.2.2 Link between working memory and attention

There is broad agreement that working memory is closely related to attention (Awh et al., 1998; Chun, 2011; Gazzaley & Nobre, 2012; Kiyonaga & Egner, 2013; Baddeley A., 1993; Kane et al., 2001). While the term "working memory" generally refers to "the mechanisms and processes that hold the mental representations currently most needed for an ongoing cognitive task available for processing" (Oberauer K., 2019), the meanings of the term attention are more diverse. One line of research defines attention as a limited resource for information processing (Kahneman, 1973; Wickens C. D., 1980). Another proposes that attention is not a resource but a process or mechanism for the selection of information to be processed with priority (Chun et al., 2011; Desimone & Duncan, 1995). This study adopts the widely accepted notion of attention as a resource, and the human cognitive system has a limited resource that can be used for carrying out the so-called attention-demanding processes. Well-defined resource concepts differ in their details, but they share a set of assumptions: a resource is a limited quantity that enables a cognitive function (e.g., holding a representation available) or process (e.g., retrieving or transforming a representation), such that its efficiency and success probability increases monotonically with the resource amount allocated to it. The resource can be allocated flexibly to a broad range of representations and processes, and it can be subdivided into portions allocated in parallel to different recipients. Resource sharing implies that prioritising one cognitive function or process occurs at the expense of others that need the same resource at the same time. It is this well-defined resource concept, rather than the unconstrained informal notion of resources, that this study considers as a possible explanation of the capacity limit.

There is considerable empirical evidence supporting the concept that working memory capacity is limited by an attentional resource (Anderson et al., 1996; Case, 1972; Just & Carpenter, 1980; Ma et al., 2014). Studies that relate working memory to an attentional resource endorse the notion that the limited capacity of working memory reflects a limited resource and that this resource also serves some or all functions commonly ascribed to attention.

This thesis relies on Cognitive Load Theory (CLT) as a main framework to study the limit of capacity in the working memory of investors in the financial market. According to CLT (Paas & Van Merriënboer, 1994; Sweller et al., 1998; Van Merriënboer & Sweller, 2005; Ayres & Paas, 2012; Sweller et al., 2011), the human cognitive architecture consists of a working memory (WM) and a long-term memory (LTM). While LTM is assumed to be virtually unlimited, WM is severely constrained in both capacity (Miller G., 1956; Cowan N., 2001) and duration (Peterson & Peterson, 1959). We can consciously process no more than a few items at a time for no longer than a few seconds. Working memory will get overloaded if these limits are exceeded. WM plays a crucial role in human cognition by allowing people to temporarily maintain and process relevant information (Baddeley A., 1992; 2012). The role of WM is significantly important in high-level cognitive tasks (e.g., mathematical problem-solving, language comprehension, or analogical reasoning) as people need to continuously process multiple pieces of relevant information and solve for immediate results. Finding the fundamental value of stocks and making sound trading decisions are examples of this kind of difficult task, which is further exacerbated when investors' WM are overwhelmed. Investors who are not aware of their limitations in processing multiple pieces of information at the same time will tend to overestimate their ability to analyse data. Therefore, it is important to gain a better insight into investors' limited WM capacity and processing power and how that affects their financial decision-making, which is the objective of this research.

2.3 Information quantity and information overload

2.3.1 Information quantity in modern financial environments

The modern financial environment exposes investors to a vast and continuous flow of potentially relevant information. Earnings announcements, annual reports, analyst commentary, macroeconomic news, media coverage, and firm-specific disclosures all compete for attention, often within a narrow decision window. In principle, more information should support better decisions by reducing uncertainty and allowing investors to form more accurate judgements. In practice, however, the benefits of additional information are not unlimited. Once the volume, diversity, or complexity of available cues exceeds what decision-makers can process effectively, additional information may no longer improve judgement and may instead reduce decision quality. This is the central concern of the information-overload literature.

At a broad level, information overload refers to a mismatch between the informational demands of a task and the cognitive resources available to process them. Early work in this area defines overload as a condition in which the amount of information confronting the decision-maker exceeds his or her processing capacity (Schroder et al., 1967; Eppler & Mengis, 2004). That basic idea has remained highly influential because it captures an important asymmetry. Information can continue to accumulate even when the decision-maker's capacity to screen, interpret, and integrate it does not. In such cases, the problem is not the existence of information itself, but the inability to use it efficiently once it becomes too abundant or too demanding.

2.3.2 Historical development of the overload literature

Although the term information overload gained prominence in the twentieth century, the underlying concern is much older. Historical reviews suggest that scholars have long worried about the consequences of having too much to read and too little time to absorb it. Blair (2012), for example, traces concerns about informational excess back many centuries, while Rosenberg (2003) shows that anxieties about proliferating books and texts intensified long before the digital era. In the twentieth century, these concerns became more explicit and more practically urgent as modern communication systems dramatically increased the volume and speed of accessible information. Bawden et al. (1999) and Bawden and Robinson (2009; 2020) show that by the mid-twentieth century, overload was already being discussed as a serious challenge for science, organisations, and professional work. What distinguishes the contemporary setting is therefore not the existence of the problem, but its scale, speed, and pervasiveness.

This historical perspective is especially relevant to finance. Investors now operate in an environment in which information is abundant, cheap to access, and often delivered continuously through multiple channels. Advances in information technology have lowered search costs and increased transparency, but they have also made it more difficult to distinguish what is diagnostic from what is merely available. In earlier periods, the core problem was often how to obtain enough information. In modern financial markets, the problem is often how to screen, prioritise, and use an excess of it. This change makes information overload especially relevant to investor decision-making.

2.3.3 The nature of information overload

The literature also makes clear that overload is not simply a matter of raw quantity. For overload to arise, the information must be sufficiently relevant or potentially useful to demand attention. If the material is clearly worthless, it can often be ignored. The difficulty arises when decision-makers face a large body of information that appears potentially informative and therefore cannot be dismissed without some degree of processing. Under those conditions, the decision-maker may begin to experience a loss of control, increased mental strain, and difficulty identifying which cues matter most. Wilson (1995), Wilson T. (2001), and Savolainen (2006; 2007) emphasise that these feelings are frequently tied to a perceived inability to access, organise, or use relevant information efficiently, often because time is insufficient. This point is important for the present thesis because the practical burden in financial settings rarely comes from quantity alone. It comes from quantity under time and under uncertainty.

A useful way to think about overload is therefore as a threshold phenomenon. Additional information can improve judgement up to a point by reducing uncertainty and broadening the evidence base. Beyond that point, however, the marginal benefits of more information begin to diminish, and the costs of processing it rise more sharply. These costs may include longer processing time, greater confusion, weaker prioritisation, higher cognitive load, and lower accuracy. This threshold logic appears repeatedly in the literature and is one of the most consistent themes across disciplines.

2.3.4 When more information stops helping

Much of the foundational work comes from research on information processing and environmental complexity. Schroder et al. (1967) show that individuals' capacity to process information does not rise indefinitely with environmental demands. Instead, performance improves with increasing complexity only up to a certain threshold, beyond which further increases lead to deterioration rather than gains. O'Reilly (1980) interprets this decline as evidence that additional information is no longer successfully incorporated into the decision process once capacity limits are reached. This basic pattern is highly relevant because it suggests that overload is not an all-or-nothing condition. It emerges gradually as task demands move beyond manageable limits.

Later work across management information systems, organisational research, and digital environments reaches a similar conclusion. Grisé and Gallupe (1999) show that electronic meeting systems intended to improve group productivity can, under some conditions, overwhelm users with too much input, thereby reducing rather than enhancing effective decision-making. Ayyagari (2012) and Lee, Son, and Kim (2016) similarly show that excessive information can contribute to technostress and digital fatigue, especially in communication-intensive environments. Swar, Hameed, and Reychav (2017) report comparable patterns in online health-information search, where excessive information can increase psychological distress. These studies arise in different settings, but the common implication is clear. When information becomes too abundant or too difficult to organise, it can weaken rather than support judgement.

2.3.5 Related evidence from choice overload

A related literature in marketing examines the idea of choice overload. This work is closely connected to information overload, though the two are not identical. Choice overload arises when the number of available options becomes so large that choosing among them becomes more difficult or less satisfying. Information overload, by contrast, can occur even when the core challenge lies in processing available cues rather than selecting from a menu of alternatives. The distinction matters because finance more often resembles the latter case. Investors are not always choosing among neatly defined options in the way consumers choose among chocolates or jams. More often, they are trying to interpret a stream of financial signals whose relevance is uncertain and whose value depends on rapid, accurate processing.

Even so, the marketing literature is useful because it reinforces the broader threshold argument. A number of studies suggest that although larger assortments can initially increase interest, perceived freedom, or attraction, they may also reduce satisfaction, lower decision quality, or discourage action once the choice set becomes too large (Iyengar & Lepper, 2000; Reutskaja & Hogarth, 2009; Schwartz, 2004). The broader implication is that more is not always better. There may be an intermediate range in which additional information or additional options are helpful, but beyond that point they generate confusion, frustration, and diminishing returns. At the same time, this literature also shows that negative effects are not universal. Some studies find that the impact depends on prior preferences, familiarity, expertise, or task structure (Chernev, 2003a; 2003b; Mogilner et al., 2008; Reutskaja et al., 2011). That nuance is helpful because it suggests that the costs of heavy information environments depend partly on who is processing the information and under what conditions.

2.3.6 Evidence from accounting and auditing

The accounting and auditing literature is even closer to the present thesis because it focuses more directly on cue-based financial judgement. A long-standing theme in this work is that increasing the number of informational cues does not necessarily improve decision quality once the task becomes cognitively demanding. Casey (1980), for example, shows that when bank loan officers are given heavier information loads in bankruptcy-prediction tasks, their accuracy does not improve, even though they spend more time processing the information. This pattern is important because it suggests that extra information may raise processing effort without yielding better outcomes. Similar concerns appear in the work of Chewning and Harrell (1990), Stocks and Harrell (1995), Tuttle and Stocks (1998), Tuttle and Burton (1999), and Swain and Haka (2000), all of whom document changes in cue utilisation, decision consistency, or information search as information loads increase. Taken together, this literature suggests that the practical manifestation of overload is not merely subjective frustration. It can also be observed in lower consistency, flatter cue usage, or declining ability to extract the most relevant information from the available set.

Table 2.1: Summary of studies of the impact of information load on cue utilization

Study	Task / participants	Info-load manipulation	Effect of higher info load
Chewning and Harrell (1990)	Financial-distress prediction / Auditors & students	3 levels of cues	Inverted-U for $\sim$1/3 of participants; overload $\rightarrow$ lower consistency
Stocks and Harrell (1995)	Financial-distress prediction / Bank loan officers	6 vs. 9 info cues	Groups $\uparrow$ cues used; individuals no change
Tuttle and Burton (1999)	Investment analysis with incentives / Undergraduate accounting students	Info load 6 vs. 9 cues	Relative cue usage declines with more info
Shields (1980)	Performance-report analysis / Corporate managers	More lines/measures in reports	Information search patterns altered under higher load
Shields (1983)	Performance-report analysis / Corporate managers	Varying info supply/demand	Absolute selection $\uparrow$, relative selection $\downarrow$

Study	Task / participants	Info-load manipulation	Effect of higher info load
Swain & Haka (2000)	Capital-budgeting decisions / MBA students	Low load: 5–6 cues; medium load: 10–12 cues; high load: 18–20 cues	Search patterns change; decision quality tended to decline under overload
Hioki, Suematsu, & Miya (2020)	Performance evaluation (Balanced Scorecard) / Managers	Simultaneous handling of many measures	High-NFC (Near Field Communication) managers stop using cues effectively under overload; low-NFC under-use customer cues regardless

This body of work also shows that overload is sensitive to how information is structured and presented. Iselin (1988) argues that information load should not be treated as a single undifferentiated construct, because diversity and cue repetitiveness can affect judgement differently. This is an important insight. It suggests that the burden of information depends not only on how much there is, but also on whether the information introduces genuinely new dimensions or simply repeats existing ones. Tuttle and Stocks (1998) make a related point by showing that numeric presentation can intensify overload relative to simpler categorical cues because numeric data require an additional interpretive step before they become meaningful. This observation is particularly relevant for finance, where decision-makers frequently work with ratios, growth rates, margins, and other numerical indicators rather than simple qualitative labels. In such environments, even a modest increase in the number of cues can substantially increase processing demands.

More recent review work reinforces the same conclusion. Roetzel (2019) and Hartmann and Weißenberger (2024) organise the overload literature around input, process, and output stages of decision-making. Their general argument is that the effects of overload cannot be understood by looking at information quantity alone. The number of cues, the clarity of those cues, the complexity of the decision rules, the time available, and the capabilities of the decision-maker all shape whether information helps or hinders performance. Once information exceeds manageable levels, judgement accuracy, confidence, consistency, and subjective ease may all deteriorate. This broader framework is useful for the present thesis because it makes clear that information quantity is one central source of strain, but not the only one. It also helps explain why overload effects are likely to interact with complexity and time pressure rather than operate in isolation.

2.3.7 Evidence from finance

Evidence from finance itself, while more limited, points in the same direction. Agnew and Szykman (2005) show that participants in defined-contribution pension settings become more likely to default to simpler options when investment choices are numerous, similar, or difficult to distinguish. Information presentation also matters. A clearer display reduces feelings of overload and improves satisfaction, whereas lower financial knowledge is associated with greater susceptibility to overload. Although pension decisions differ from the short-horizon financial tasks in the present thesis, the underlying implication is similar. When financial information becomes too abundant or too difficult to organise, people may fall back on simplified rules or default strategies rather than conduct a fuller evaluation.

More recent work on corporate disclosure suggests that the same logic applies to professional users of financial statements. Impink, Paananen, and Renders (2022) show that additional mandatory disclosure can initially improve analyst performance, but that these benefits reverse beyond a certain point. As disclosure volume rises further, analysts become slower, less accurate, and more dispersed in their forecasts, particularly when they have fewer resources or cover many firms. This inverted-U pattern is especially useful for the present thesis because it captures the central intuition of the overload literature in a finance-specific setting. More information may be helpful initially, but once it exceeds manageable limits, performance begins to deteriorate.

Taken together, these literatures suggest three broad conclusions. First, information quantity matters because additional cues can impose real cognitive costs even when the information is potentially useful. Second, the relationship between information and performance is unlikely to be linear. More information may improve performance up to a point, but beyond that point, additional information may become counterproductive. Third, the onset and severity of overload depend on the surrounding decision environment, including time pressure, task structure, numerical complexity, and the capabilities of the decision-maker. These conclusions are highly relevant to financial decision-making, where investors often have to combine multiple cues quickly and where the cost of delayed or inaccurate judgement can be substantial.

2.3.8 Distinguishing information quantity from information overload

It is also important to distinguish information quantity from related concepts. Information quantity refers primarily to how much information is available to the decision-maker. Information overload refers to the state in which that quantity, often together with other demand characteristics, exceeds what can be processed effectively. The two are closely related, but they are not identical. A large quantity of information does not always produce overload, especially when the task is simple, the time available is ample, or the decision-maker is highly skilled. Conversely, overload may arise even at moderate levels of information if the cues are difficult to interpret, numerically demanding, or embedded in a complex task. This distinction matters for the present thesis because it allows information quantity to be treated as a manipulable feature of the task, while overload remains the broader cognitive condition that may emerge when that quantity becomes too demanding.

This distinction also helps clarify the relationship between information quantity and limited attention. Limited attention is the broader constraint arising from finite cognitive resources. Information overload is one important way in which that constraint becomes behaviourally consequential. When the number of cues increases, decision-makers must divide attention more thinly across available information, which raises the likelihood that some relevant cues will be ignored, underweighted, or processed superficially. In that sense, the literature on information overload can be understood as specifying one route through which attentional constraints translate into poorer decision outcomes.

2.3.9 Relevance to the present thesis

Despite the breadth of this literature, an important gap remains. Much of the existing evidence comes from consumer choice, accounting judgement, pension-plan selection, or analyst responses to lengthy reports. These studies are highly informative, but they do not directly examine how investors perform when they must process several pieces of numeric firm information under explicit time pressure and varying task complexity. They also do not always separate information quantity cleanly from other dimensions of task difficulty. As a result, less is known about how additional financial information affects investor decision quality at the point of individual judgement when the task is both time-constrained and analytically demanding.

The present thesis addresses that gap by focusing directly on information quantity in a controlled financial decision environment. Participants are asked to calculate stock intrinsic value and make trading decisions while the amount of information available varies across conditions. This design makes it possible to examine whether heavier information loads reduce decision quality and increase subjective mental effort, and whether these effects become stronger when the broader task environment is also demanding. In this way, the study moves beyond the general claim that more information can be harmful and examines more precisely when additional financial information ceases to help and begins to hinder performance.

In a financial task of this kind, the expected implication is straightforward. As information quantity rises, investors should find it harder to identify, organise, and integrate all relevant cues accurately within the available time. Heavier information loads should therefore reduce decision quality while increasing perceived mental effort.

2.4 Time constraint and its effects on decision-making

2.4.1 Time as a core resource in information processing

Information overload is often understood as a mismatch between the demands of a task and the resources available to cope with those demands. In its classic form, this idea is rooted in the information-processing view of organizations developed by Galbraith (1974) and extended by Tushman and Nadler (1978). On this view, overload occurs when information-processing requirements exceed information-processing capabilities. This formulation is especially useful because it makes clear that the informational burden does not depend only on the amount of information present. It also depends on whether the decision-maker has sufficient resources to gather, interpret, and synthesise that information into a judgement within the time available.

This point is particularly relevant in financial settings. Investors rarely process information in a temporally neutral environment. They often face time-sensitive disclosures, competing signals, and the practical need to respond before the value of the information decays. As a result, time is not simply an external condition surrounding the task. It is one of the core resources that determines whether the available information can be processed effectively. A set of cues that is manageable under a relaxed time condition may become far more demanding when the same cues must be interpreted quickly. In that sense, the burden of information is inseparable from the amount of time allowed for dealing with it.

This resource-based interpretation is important for the present thesis because it clarifies why time matters even when information quantity is held constant. A decision-maker may, in principle, be capable of processing a given financial problem, yet still perform poorly if the available time is too short to permit careful integration of the relevant cues. The issue is therefore not only how much information is available, but also whether the decision-maker has enough time to use it effectively.

2.4.2 Time pressure and information overload

A useful distinction here is between cognition-related and resource-related overload. Eppler and Mengis (2004) note that the literature has paid far more attention to cognition-related explanations, which focus on bounded attention and limited memory, than to resource-related explanations, which focus on practical constraints such as time and budget. Yet from a resource perspective, time is decisive. Overload may arise not because decision-makers lack the ability to process the information in an abstract sense, but because they cannot do so within the time available.

Roetzel (2019) sharpens this point by defining information overload as a state in which a set of informational cues inhibits the decision-maker's ability to arrive at the best possible decision because scarce individual resources are constrained. Those scarce resources may include cognitive characteristics, such as limited short-term memory and serial processing ability, but they may also include task-related resources, especially time. This broader framing is useful because it places time alongside memory and attention as one of the core constraints shaping decision quality.

This perspective also helps distinguish between time constraint and time pressure. A time constraint is an objective feature of the task, namely the amount of time available for completion. Time pressure, by contrast, refers to the subjective experience induced by that constraint. Two people facing the same deadline may not feel the same degree of pressure, and the same deadline may feel tight in one task but manageable in another. For the present thesis, this distinction matters because the experimental design manipulates time constraints directly, while time pressure is the psychological state expected to emerge from those constraints. That approach is preferable to treating the two ideas as interchangeable.

2.4.3 How time pressure changes decision processes

The broader decision-making literature suggests that time pressure changes not only how much information people process, but also how they process it. A consistent finding is that when time becomes scarce, decision-makers adapt by filtering information more aggressively, narrowing their search, and simplifying their strategy. These responses may help preserve speed, but they often reduce analytical depth.

Zur and Breznitz (1981) show that under time pressure individuals tend to filter information and accelerate the decision process in order to cope with the deadline. Wright (1974), in his study of the "harassed decision maker", similarly argues that time-constrained individuals focus more selectively on particular types of information and may rely on simpler decision rules that allow them to eliminate options quickly rather than evaluate them comprehensively. Mann and Tan (1993) reach a comparable conclusion in an experimental setting, showing that time-pressured participants inspect less information and focus more heavily on cues they regard as especially important.

Taken together, these studies suggest that time pressure induces a more selective and compressed mode of information processing. Rather than fully evaluating all available evidence, decision-makers tend to screen more aggressively and concentrate on a narrower set of cues. This adaptation may be functional in the sense that it helps preserve speed, but it also increases the risk that relevant information will be overlooked or insufficiently integrated.

2.4.4 Time pressure, strategy shifts, and decision quality

A related literature examines how time pressure affects decision strategies more directly. Payne, Bettman, and Luce (1996) argue that under time constraints individuals often shift from more effortful, compensatory approaches to simpler, non-compensatory strategies. Instead of weighing multiple attributes carefully, they may rely on heuristics such as elimination-by-aspects, satisficing, or other rules that reduce the number of comparisons required. This shift reflects a trade-off between effort and accuracy. When time is scarce, decision-makers often prioritise methods that are less mentally demanding, even if those methods do not use all of the available information.

Edland and Svenson (1993) draw a similar conclusion and suggest that time pressure often changes both the depth and the style of processing. Later work suggests that responses to time pressure are conditional rather than uniform. Claessens et al. (2007) indicate that time-management practices may be more useful for some individuals and work settings than others, Maruping et al. (2015) show that the effects of time pressure on teams depend on temporal leadership, and Eisenhardt (1989) finds that successful fast decision makers in high-velocity environments may use more, rather than less, information and consider more alternatives. Taken together, these studies suggest that tighter deadlines do not affect all decision makers in the same way, and that the consequences of time pressure depend importantly on the capabilities and structures available to cope with it.

Wu et al. (2022), using bandit tasks under varying time conditions, show that time constraints reduce exploratory behaviour, weaken sensitivity to expected rewards, and increase repetition of prior choices. Their results suggest that time-pressured individuals become more conservative and less flexible. Khetarpal and Singh (2024) likewise show that time-limited messages can create urgency and prompt quicker decisions, often through fear of missing out and related psychological mechanisms. Although this latter setting is consumer-oriented rather than financial, the underlying mechanism is familiar. When time becomes scarce, individuals are pushed toward faster, less deliberative responses.

2.4.5 Evidence from accounting and auditing

The link between time and information load has long been recognised in accounting and auditing research. Time has been used as a metric for quantifying information load, as an experimental condition affecting the processing of financial information, and as an indirect indicator of decision-making performance (Abdel-Khalik, 1973; Casey, 1980; Iselin, 1988; Snowball, 1980; Wright, 1974). This literature is especially relevant because accounting and auditing tasks, much like the tasks in the present thesis, involve processing multiple pieces of information under practical constraints.

Schick, Gordon, and Haka (1990) go further by arguing that time may be the most critical factor in understanding information overload. Their work suggests that the experience of overload is shaped not only by the volume of information, but also by frequent interruptions and stringent deadlines. This is an important insight because it shifts attention away from the simple idea that overload is caused only by "too much information". A decision-maker may feel overloaded because the time available is too fragmented or too short to allow coherent integration of the available cues.

Later work in auditing points in the same direction. Sweeney and Summers (2002) show that heavy time demands during the busy season are associated with significantly higher emotional exhaustion and depersonalisation among public accountants. Although burnout is not the same as immediate decision quality, this evidence is still informative because it suggests that persistent time pressure imposes real psychological costs and can weaken the conditions needed for careful judgement. Lambert and Agoglia (2011) similarly show that auditors under high time pressure are less likely to revisit and integrate information from earlier stages of a multi-stage task. This weakens their ability to "close the loop" across stages and reduces audit quality. The underlying logic is highly relevant to the present thesis. When time is tight, decision-makers may focus on immediate task completion rather than on full integration of the relevant information, which can lead to more fragmented and less accurate judgements.

2.4.6 Evidence from finance and experimental economics

Finance-specific evidence, while still relatively limited, broadly supports the same conclusion. Zhang et al. (2021), using field data from peer-to-peer lending markets, show that investors who take longer before committing to a loan tend to achieve better outcomes, whereas rushed decisions are associated with lower profitability and greater exposure to high-risk loans. This suggests that faster decisions are not necessarily better decisions, particularly when the task requires meaningful risk assessment.

Nursimulu and Bossaerts (2014) also show that severe time constraints can alter financial decision-making by increasing impulsiveness and changing the way participants respond to risk and skewness. Kocher and Sutter (2006), in an experimental beauty-contest setting, find that participants under lower time pressure converge more quickly toward equilibrium and achieve better outcomes than those under tighter time constraints. These studies arise in different finance-related environments, but they converge on a similar implication. Tight deadlines can distort judgement by narrowing analysis, increasing impulsiveness, or pushing decision-makers toward simpler strategies that do not fully exploit the available information.

This broader pattern is consistent with behavioural accounts suggesting that time pressure can burden decision makers both cognitively and emotionally. Rather than simply shortening the time available for analysis, it may also increase anxiety, stress, and the need to cope with the task in a more economical way. Maule, Hockey, and Bdzola (2000) support this view by showing that deadlines increase anxiety and shift information processing toward acceleration and filtration. Sussman and Sekuler (2022) extend the argument by showing that even perceived time pressure, in the absence of objective changes to the task, increases stress and negative affect while reducing cognitive inhibition. For financial judgement, the implication is important. When time becomes scarce, performance may deteriorate not only because there is less opportunity to think, but also because the pressure itself diverts cognitive resources away from careful integration of relevant information.

2.4.7 Mixed and conditional effects of time pressure

At the same time, the literature does not suggest that time pressure is uniformly harmful in every setting. Some studies report more conditional or even apparently beneficial effects. Ahituv, Igbaria, and Sella (1998), for instance, show that time pressure impairs the performance of less experienced decision-makers more than that of highly experienced ones. This suggests that expertise may partly offset the costs of reduced time. Conte, Scarsini, and Sürücü (2015) likewise find that not all participants are strongly affected by time limitations in queueing tasks.

Recent studies suggest that time pressure does not necessarily intensify every bias. In software testing, Salman et al. (2019) find confirmation bias overall, but no evidence that time pressure increased confirmatory responding. In truth-judgement tasks, Nadarevic et al. (2021) find that time pressure did not increase the truth effect. In misinformation judgments, Sultan et al. (2022) similarly show that time pressure did not alter overall response bias and slightly reduced the familiarity-based tendency to judge information as true. These findings suggest that the effects of time pressure on bias are conditional rather than uniform, depending on the task, the underlying cue structure, and the specific bias being measured.

A particularly relevant recent study is Cao, Li, and Niu (2022), who examine how different time limits affect the disposition effect in experimental asset markets. Their results show that a tighter deadline reduces the disposition effect, whereas a looser deadline does not differ significantly from the no-constraint condition. Importantly, the shorter deadline also produces significantly higher self-reported time pressure, which helps separate the objective time limit from the psychological experience it generates. This study is useful for the present thesis for two reasons. First, it shows that different time constraints do not necessarily induce meaningfully different pressure unless the shorter condition is sufficiently tight. Second, it suggests that time pressure may alter behaviour in more complex ways than simply reducing all dimensions of decision quality. In some contexts, tighter pressure may reduce a specific bias rather than intensify it.

2.4.8 Distinguishing time constraint from time pressure

These mixed findings underscore the importance of clearly separating the objective and subjective aspects of time. A time constraint refers to the actual deadline imposed by the task. A time pressure effect arises when that deadline creates a felt sense of urgency that alters cognition, behaviour, or both. This distinction matters because prior studies do not always clearly separate the two. Some compare time-limited conditions with no time limit, while others manipulate the deadline's duration but describe the effect simply as "time pressure," without demonstrating whether the shorter deadline actually induced a meaningfully different psychological state.

For the present thesis, this distinction is built directly into the design. The study uses two different time conditions rather than a simple constrained versus unconstrained comparison. This allows the analysis to ask not only whether time matters, but whether a tighter objective deadline produces sufficiently greater time pressure to affect performance. That approach follows the logic of Cao et al. (2022), where the shorter deadline produced a substantively different pressure experience while the looser deadline approximated a low-pressure condition.

2.4.9 Relevance to the present thesis

The present thesis examines financial decision-making under two time conditions. In the shorter condition, participants have three minutes to calculate the intrinsic value of a stock and make a trading decision. In the longer condition, participants have five minutes, which is roughly 70% more time than in the shorter condition. Pilot evidence suggests that the three-minute condition is sufficiently tight to induce meaningful time pressure, whereas the five-minute condition is more relaxed and yields performance closer to that observed in an effectively low-pressure setting.

This design contributes to the literature in several ways. First, it provides a clearer test of how varying degrees of time constraint shape investor judgement in a financial task that requires both valuation and decision choice. Second, it allows time pressure to be examined alongside other sources of cognitive demand, especially information quantity and task complexity. This is important because the effects of time are unlikely to operate in isolation. A deadline that is manageable under a simple information set may become much more consequential when the decision-maker must process more cues or integrate them in a more complex task. Third, the design helps address a relative gap in finance, where time pressure is clearly important in practice but still less directly examined than in psychology, accounting, or general decision research.

These arguments suggest that time is not simply a background feature of the task. It is one of the core resources through which decision quality is shaped. When available time is reduced, investors should have fewer opportunities to screen, verify, and integrate financial information carefully, making poorer judgement and higher perceived effort more likely.

2.5 Task complexity

2.5.1 Why task complexity matters in financial decision-making

Task complexity is central to this thesis because the demands investors face depend not only on how much information is available, but also on how difficult that information is to organise, interpret, and integrate into a decision. In financial settings, this distinction is especially important. Two tasks may contain a similar amount of information, yet one may be substantially more demanding if it requires more calculations, more cross-checking, or more integration across interdependent cues. In that sense, decision difficulty does not arise from information quantity alone. It also depends on the structure of the task and the relationships among its elements.

This point matters because many financial decisions are not simple cue-recognition tasks. Investors often need to combine several indicators, understand how those indicators relate to one another, and translate that interpretation into a valuation or trading judgement. When the number of steps increases, when the relationships among cues become less transparent, or when the decision requires more coordination across pieces of information, the task becomes more complex. That added complexity can place pressure on working memory and attentional control even before the amount of information becomes very large.

Complexity is therefore especially relevant in financial decision-making because the task often involves both numerical processing and integration across cues. Investors do not merely observe information. They must decide which cues matter, determine how those cues fit together, and use them to arrive at a coherent judgement. This makes task complexity more than a background feature of the decision environment. It is one of the main channels through which financial problems become cognitively demanding.

2.5.2 Defining and conceptualising task complexity

Although task complexity is widely discussed, the concept is not defined in one uniform way. The literature contains multiple definitions and models, and these do not always refer to precisely the same underlying phenomenon. This is one reason the literature can feel fragmented. Researchers often agree that complexity matters, but they do not always mean the same thing when they use the term.

Broadly, three perspectives can be distinguished. Structuralist approaches define complexity in terms of the objective features of the task itself. Resource-based approaches focus on the amount and type of cognitive resources required to complete the task. Interactionist approaches place greater emphasis on the relationship between the task and the person performing it, including experience, skill, and subjective perceptions of difficulty. This diversity is useful because it shows that complexity is multidimensional, but it also creates ambiguity. In some studies, complexity refers mainly to the number of task elements. In others, it refers to ambiguity, uncertainty, dynamic change, or felt difficulty.

For the purposes of this thesis, the structuralist perspective provides the most appropriate starting point. From this viewpoint, complexity arises from the objective features of the task, especially the number of components involved and the degree of interdependence among them. A task becomes more complex when it contains more elements, when those elements are more tightly connected, or when they must be processed in a carefully sequenced way. This perspective is especially useful in an experimental setting because it allows complexity to be manipulated through task design rather than inferred only from how difficult participants say the task feels.

Wood's framework is particularly influential here. Wood (1986) argues that complexity depends on the number of distinct acts required, the number of informational cues that must be processed, and the relationships among those acts and cues. He distinguishes among component, coordinative, and dynamic complexity. Component complexity refers to the number of acts or pieces of information involved. Coordinative complexity refers to the extent to which those elements must be integrated or sequenced correctly. Dynamic complexity concerns the extent to which task relationships change over time. This framework is useful because it shows that complexity does not arise from quantity alone. A task may be demanding because it contains many pieces, because those pieces must be coordinated carefully, or because the underlying structure is unstable.

Campbell (1988) offers a related account, but places greater emphasis on multiple solution paths, multiple outcomes, conflicting interdependence, and uncertainty. Bonner (1994), working in auditing, distinguishes among input complexity, processing complexity, and output complexity. That framework is especially helpful because it shows that a task may be difficult even when the amount of information itself is not extreme. Complexity can also arise because the rules linking information to judgement are demanding, or because the required output is precise and cognitively taxing. Taken together, these models point to a common idea. Complexity rises when decision-makers must handle more elements, more interdependencies, or less transparent pathways from information to judgement.

2.5.3 Complexity and cognitive processing

The literature suggests that task complexity matters because it changes how decision-makers allocate attention and use cognitive resources. As complexity rises, individuals must keep track of more elements, coordinate more relationships, and carry out more mental operations. This places greater pressure on working memory, which is limited in capacity and becomes more vulnerable to overload when several items or operations must be handled at once. Greater complexity may therefore reduce decision quality not only because the task contains more moving parts, but also because it becomes harder to maintain a coherent mental representation of how those parts fit together.

Evidence from neuroscience supports this general mechanism. Research on visual short-term memory and visual working memory suggests that memory capacity depends not only on the number of items being processed, but also on the complexity of those items. Alvarez and Cavanagh (2004), for example, show that memory capacity is lower for more complex stimuli than for simpler ones, which suggests that complex objects consume more processing resources per item. Eng, Chen, and Jiang (2005) reach a similar conclusion and report that visual working memory capacity falls as the perceptual complexity of objects rises. Song and Jiang (2006) further show that more complex visual features and feature conjunctions recruit broader neural resources than simpler features, which is consistent with the idea that complexity raises cognitive demands at the processing stage itself. Taken together, these studies suggest that complexity can reduce effective working-memory capacity by increasing the resource cost of each item or operation.

This general mechanism is relevant beyond the visual domain. Higher-complexity stimuli typically require more working-memory resources to process and manipulate, which means that performance may deteriorate even when the absolute amount of information remains unchanged. In practical decision settings, the implication is that a task can become harder not only because there is more information, but because each piece of information is more demanding to interpret, combine, or verify. For financial decisions, that point is especially important because investors often work with numeric cues that require active transformation rather than passive recognition.

Complexity may also affect attention allocation more directly. When a task involves several interdependent steps, individuals must decide where to focus first, which operations require checking, and how much effort to devote to each part of the task. As complexity rises, the burden of this coordination itself becomes cognitively costly. Decision-makers may therefore simplify, omit, or mis-sequence parts of the task, not necessarily because they lack information, but because the overall structure is difficult to manage within limited cognitive capacity.

2.5.4 Complexity and performance

A large body of research across several disciplines suggests that higher task complexity is often associated with lower performance, particularly when decisions require the integration of multiple cues under limited cognitive resources. One reason is that complex tasks make it harder for individuals to apply fully compensatory strategies in which all available information is weighed carefully. Instead, decision-makers often simplify as demands rise.

This pattern appears clearly in psychology and behavioural decision research. Tversky and Kahneman (1981) suggest that when practical decision problems are framed in more complex ways, individuals may struggle to integrate all relevant aspects of the choice, which can produce more variable and less consistent decisions. Payne (1976) provides a particularly influential demonstration of strategic adaptation under complexity. As the number of alternatives and attributes increases, participants shift away from more exhaustive, compensatory processing and toward simpler, non-compensatory strategies. In other words, decision strategies are not fixed. They adapt to task demands, often in ways that conserve cognitive effort but sacrifice analytical completeness.

Related work in consumer decision-making points in the same direction. Lussier and Olshavsky (1979) show that as the number of brands and attributes increases, consumers alter their information-processing strategies to cope with the added burden. Rather than evaluating all available information in a balanced way, they become more selective and more structured in their search. Kim and Khoury (1987) report similar patterns for married couples, suggesting that the effect is not limited to isolated individual choice. More recent work continues to support the view that decision strategies adapt to task complexity. For example, Swait and Adamowicz (2001) model strategy switching as a function of cognitive burden, Meißner et al. (2020) show with eye tracking that larger choice sets induce more filtration and altered search patterns, and Jang et al. (2022) find that higher task complexity increases selective information reduction, especially for lower-ability decision makers. Together, these studies suggest that complexity changes the process of information acquisition and evaluation, often before any final reduction in observed choice quality is assessed.

The auditing and accounting literatures provide evidence that is even closer to the present thesis because they involve judgement under information-rich and professionally consequential conditions. Bonner (1994) argues that increased task complexity, arising from factors such as ambiguity, poor cue clarity, or greater informational burden, can produce cognitive overload and reduce judgement quality. Tan and Kao (1999) similarly show that as task complexity rises, higher levels of knowledge and problem-solving ability are needed before accountability improves performance. This is an important qualification. Complexity does not affect all decision-makers identically, but the general implication remains that harder tasks require more capability if performance is to be maintained. Hwang and Lin (1999) also show, through a meta-analysis of bankruptcy-prediction studies, that greater information diversity is associated with lower decision quality. Although their focus is on information load rather than complexity in a narrow structural sense, the mechanism is related. As the variety and complexity of available cues increase, maintaining a high-level judgement becomes harder.

Human-computer interaction research points in a similar direction. Jacko and Ward (1996) show that adding more task-complexity constructs to a psychomotor interface increases response times and impairs performance, which they link to greater short-term memory demands. More recent work on database-query tasks also reaches similar conclusions. Topi, Valacich, and Hoffer (2005) find that as query tasks become more complex, users make more errors, complete fewer queries per minute, and report lower confidence. Within their experimental range, task complexity appears to matter more than time availability limitations. Taipalus (2020) likewise shows that students achieve lower SQL success rates when database schemas are more logically complex and structurally interrelated. These studies are not finance studies, but they are relevant because they involve structured, data-intensive tasks that require accurate coordination of multiple elements.

Taken together, these literatures suggest a fairly consistent pattern. As tasks become more complex, people often spend more effort, rely on more selective processing strategies, and become more prone to error. The negative effect appears especially likely when the task requires several interdependent steps, precise integration across cues, or the transformation of complex inputs into a definite output. These are all features commonly found in financial analysis and valuation tasks.

2.5.5 Why the relationship may not always be strictly linear

Even so, the literature does not suggest that the complexity-performance relationship is always simple or uniformly negative. Under some conditions, greater complexity may support learning, engagement, or the development of more effective strategies rather than merely depressing performance. In an accounting setting, Mascha (2001) shows that complex cases can produce greater acquisition of procedural knowledge than simple cases when participants receive expert-system feedback, suggesting that added processing demands can become instructionally useful when guidance is available. More recent work points in a similar direction. Zeitlhofer et al. (2024) find that consistently high task complexity improved immediate performance, germane cognitive load, and meta-awareness, while not reducing intrinsic interest. Li et al. (2024) likewise show that task-related complexity positively influences employee learning from AI and strengthens the positive association between AI use and learning. In an educational context, Namaziandost and Çelik (2025) further report that systematically varied task complexity can improve targeted learning outcomes, with qualitative evidence of stronger engagement and motivation. Earley et al. (1990) provide a useful organisational qualification. They do not suggest that complexity is beneficial in itself, but they do show that in jobs high in task component complexity, experience strengthens the positive relation of goal setting to task strategy quality and performance. Taken together, these studies suggest that complexity can sometimes promote deeper processing and better learning-related outcomes, particularly when it is paired with support, experience, or an enabling structure, rather than being treated as uniformly harmful.

These findings are important, but they should be interpreted carefully. Much of this positive evidence comes from learning, motivation, or repeated-job contexts, where moderate increases in complexity may make a task more engaging and therefore support effort, strategy development, or skill acquisition. That is not the same as saying that complexity generally improves immediate decision accuracy in short-horizon analytical tasks. The key distinction is between complexity as a source of challenge that may promote development over time, and complexity as an immediate burden on working memory and information integration at the moment of decision.

This distinction helps explain why some researchers have proposed a curvilinear relationship between complexity and performance. Driver and Streufert (1969) argue that systems may respond to input load in an inverted-U pattern, where moderate levels of complexity foster higher integrative complexity and more effective processing, but very low or very high levels reduce performance. Wood (1986) similarly suggests that increases in complexity may initially enhance challenge and activation, yet later become harmful once task demands exceed performer capabilities. Bonner (1994) also finds some evidence of a quadratic relationship in ratio-analysis tasks, although the pattern is not consistently significant across all task types. More broadly, Liu and Li (2012) note that curvilinear findings are more often observed in interface or visual-complexity research than in the broader task-complexity literature.

2.5.6 Evidence from finance and economics

Compared with the wider complexity literature, finance-specific evidence remains more limited, especially for numerical decision tasks at the individual level. Even so, existing work broadly suggests that greater complexity can deter attention, distort judgement, and weaken market responses.

One stream of research focuses on textual and disclosure complexity. Cohen et al. (2020) show that textual changes in corporate reports, particularly in risk-factor language and negative sentiment, contain information that predicts future returns, which suggests that investors do not fully process these signals at the time of release. One plausible explanation is that increased length and complexity make it harder for investors to promptly recognise the informational content of these reports. Umar (2022) provides more direct evidence on investor attention by showing that more complex headlines attract fewer article views and weaker immediate market responses. The effects are strongest among less-sophisticated investors and during low-attention periods, which suggests that complexity interacts with attentional limits rather than operating in isolation.

Related work suggests that complexity can also be used strategically. Carlin (2009) shows theoretically that firms may introduce price complexity in order to weaken consumers' ability to compare options, thereby sustaining higher prices even in competitive settings. Kalaycı and Potters (2011) provide experimental evidence consistent with this logic, showing that buyers make poorer choices as product attributes increase, even when those attributes do not change product value. Lo, Ramos, and Rogo (2017) similarly find that firms engaging in earnings management tend to produce less readable reports, which is consistent with the obfuscation view that complexity may be used to conceal rather than clarify. Bushee and Huang (2024) refine this point by distinguishing between informative complexity and obfuscatory complexity in conference-call language. Their results suggest that analysts are often better able than investors to extract value-relevant signals from complex language, which implies that complexity may slow or distort market interpretation even when the information itself is potentially useful.

DeHaan et al. (2021) extend this argument to mutual fund disclosures and fee structures. They show that high-fee funds tend to produce less readable disclosures and more complicated fee arrangements, which likely make it harder for retail investors to assess fund quality accurately. Jin et al. (2022) provide related laboratory evidence that senders sometimes choose unnecessarily complex disclosures strategically, and that receivers make more systematic mistakes when faced with those disclosures. Taken together, these studies suggest that complexity matters in finance not only because it raises cognitive demands, but also because it can alter market behaviour, obscure value-relevant information, and sometimes be deployed strategically by information providers.

At the same time, much of this finance evidence concerns textual, disclosure, or product complexity rather than the type of structured numerical problem studied in the present thesis. As a result, an important gap remains. We know that complexity can deter attention and impair interpretation in market settings, but we know less about how it affects investor performance when individuals must carry out calculations, integrate several cues, and make valuation and trading decisions under explicit time limits.

2.5.7 Distinguishing complexity from information quantity

It is important to distinguish task complexity from information quantity because the two are closely related but not identical. Information quantity refers primarily to how much information is available to the decision-maker. Task complexity refers to how difficult that information is to organise, interpret, and integrate into a judgement. A task may therefore become more demanding because it contains more cues, because the relationships among those cues are more intricate, or because both conditions occur together. Treating these as separate constructs is important both conceptually and empirically.

This distinction matters because the same quantity of information can give rise to very different levels of task difficulty. A decision-maker may face several cues that are simple, independent, and easy to combine, in which case the task may remain relatively manageable even when information quantity is moderate. By contrast, a task involving a similar number of cues may become much more demanding if those cues must be processed in sequence, reconciled across several calculation steps, or interpreted in relation to one another. In that case, the difficulty arises not only from how much information is present, but from the structure of the task itself.

The distinction is equally important in the other direction. A task may become more complex even when information quantity changes only modestly. Additional complexity may arise because more operations are required, because the links among cues are less transparent, or because the decision-maker must coordinate several intermediate judgements before arriving at a final answer. In such cases, increasing difficulty does not simply reflect heavier informational volume. It reflects the greater structural demands imposed by the task.

This conceptual separation is especially important for the present thesis because both information quantity and task complexity are central explanatory variables. If they are not distinguished clearly in the literature review, the reader may reasonably wonder whether task complexity is simply another label for a larger amount of information. This thesis instead treats them as distinct but related sources of cognitive demand. Information quantity captures how much information is presented. Task complexity captures how demanding it is to process that information accurately and coherently. This distinction helps clarify the logic of the experimental design and strengthens the interpretation of the empirical results.

2.5.8 Complexity, limited attention, and information overload

The relationship between task complexity, limited attention, and information overload is also important. Limited attention is the broader constraint arising from the fact that cognitive resources are finite. Decision-makers cannot attend fully to all available stimuli at once, and they must therefore allocate attention selectively across competing cues. Task complexity becomes relevant within this broader framework because it affects how intensively those limited resources must be used. As complexity rises, decision-makers must devote attention not only to more information, but also to more operations, more interdependencies, and more difficult forms of integration. In that sense, complexity makes the consequences of limited attention more pronounced.

This point helps explain why task complexity can impair performance even when the amount of information is not unusually large. A moderately sized information set may still be difficult to process if the task requires several calculation steps, the coordination of multiple cues, or careful sequencing across interdependent elements. Under such conditions, attention must be distributed across a larger number of mental operations, which increases the likelihood that some steps will be rushed, omitted, or handled superficially. Complexity therefore does not simply add difficulty in a general sense. It changes the way in which limited attentional resources are consumed.

A similar logic connects complexity to information overload. Information overload is often described in terms of excessive quantity, but quantity alone does not determine whether overload occurs. A decision-maker may cope reasonably well with a large amount of simple, well-structured information, yet struggle with a smaller set of cues when the task requires difficult integration or numerically demanding transformations. Task complexity, therefore, helps explain why overload can arise even when information volume is only moderate. It is one of the factors that determines whether the available information remains manageable or becomes cognitively overwhelming.

This perspective is useful for the present thesis because it links the complexity literature to the broader arguments developed earlier in the chapter. Limited investor attention provides the general cognitive foundation, while information overload describes one important condition in which those limits become behaviourally consequential. Task complexity fits into this framework as a mechanism that intensifies the burden placed on finite cognitive resources. The more complex the task, the harder it becomes to allocate attention efficiently and to integrate all relevant cues before making a judgement.

2.5.9 Relevance to the present thesis

This literature provides a strong foundation, but it also leaves an important gap. Much of the prior evidence comes from neuroscience, psychology, consumer choice, auditing, or interface-based tasks. The finance literature, while growing, still focuses more often on textual complexity, disclosure readability, or product design than on structured numerical decision problems. As a result, relatively little is known about how variations in task complexity affect investor performance when individuals must calculate values, integrate multiple cues, and make trading decisions under explicit time constraints.

This gap is important because many real financial decisions are both numerically structured and time-sensitive. Investors often need to combine several firm characteristics, perform multiple calculation steps, verify the internal consistency of their reasoning, and translate those assessments into a concrete decision. In such settings, complexity is likely to matter in a particularly direct way. A task that requires more steps and more interdependent cue integration may consume more working-memory resources, increase the risk of error, and leave less capacity for reflection or verification.

The present thesis addresses this issue by examining complexity in a controlled financial decision environment. Following the structuralist tradition, task complexity is manipulated by varying the number of calculation steps and the number of information cues required to complete the task, consistent with Wood's (1986) findings. This approach makes it possible to examine whether more complex financial problems reduce decision quality and increase perceived mental effort, and whether those effects become stronger when investors simultaneously face heavier information loads and tighter time constraints. That last point is especially important. Complexity may not only impair performance directly. It may also make decision-makers more vulnerable to time pressure because complex tasks leave less slack for checking, integrating, and correcting their judgements.

What remains less clear is how these complexity effects operate in short-horizon financial tasks that require valuation, cue integration, and decision choice under explicit time constraints. Much of the existing evidence comes from psychology, auditing, consumer choice, or interface-based tasks rather than from controlled financial decision environments. This makes it important to examine whether greater structural complexity impairs investor judgement directly when individuals must carry out calculations, combine multiple cues, and reach a decision within limited time.

2.6 Irrelevant information

2.6.1 Why irrelevant information matters in financial decision-making

A related but distinct challenge in information-rich decision environments is the presence of irrelevant information. The issue here is not simply that decision-makers face a large quantity of information, but that some of the available cues do not assist with the task at hand and may nevertheless attract attention, consume processing capacity, or distort judgement. In financial settings, this problem is especially important because investors rarely encounter information that is neatly pre-classified as useful or useless. Instead, they often face a mixture of cues that appear potentially informative, even when only some of them are genuinely relevant for valuation or trading decisions.

This matters because decision-makers operate under limited cognitive resources. When attention and working memory are finite, processing irrelevant material is not costless. Time and mental effort devoted to non-diagnostic cues are resources that cannot be devoted to more informative signals. In that sense, irrelevant information does more than merely add noise. It can reduce the clarity of the decision environment and make it more difficult for investors to identify, prioritise, and integrate the cues that genuinely matter.

The relevance of this issue has increased in modern financial environments. Investors are now exposed to a continuous flow of disclosures, commentary, managerial narratives, media reports, and online discussion. Some of this information may be highly diagnostic. Some may be only weakly related to the underlying economic value of the firm. Some may simply distract from the core task. The practical burden therefore lies not only in obtaining information, but also in screening it efficiently. This makes information irrelevance an important part of the broader problem of investor judgement under limited attention.

2.6.2 Diagnosticity and the value of information

The concept of diagnosticity is central to understanding why irrelevant information matters. Information is diagnostic when it helps distinguish meaningfully between alternative judgements or outcomes. In other words, it is useful to the extent that it improves inference. Conversely, non-diagnostic information may appear informative while contributing little to an accurate judgement. This distinction is important because decision-makers do not always weigh information according to its true usefulness.

Tversky and Kahneman (1974) make this point in their discussion of representativeness and base-rate neglect. Their broader argument is that individuals often judge the likelihood of an outcome on the basis of similarity or salience rather than on the basis of what is statistically most informative. Specific details may therefore attract disproportionate weight even when they add little to predictive accuracy.

This insight is highly relevant to financial decision-making. Investors may be drawn to salient or intuitive firm characteristics that seem meaningful, while underweighting the variables that are more directly useful for valuation or expected-return assessment.

The key issue is not simply that people make mistakes. It is that they may mistake vividness or intuitiveness for diagnostic value. In financial contexts, this problem can be especially acute because many available cues appear superficially plausible. A firm's narrative, image, size-related features, or public visibility may seem informative even when they add little to the immediate valuation task. Under those conditions, the challenge becomes one of discrimination. Decision-makers must distinguish what is genuinely helpful from what is merely attention-grabbing.

This conceptual distinction is important for the present thesis because the financial problems faced by participants include cues that may appear meaningful but are not required for the core decision task. The relevant question is therefore not simply whether participants can process more information, but whether they can identify which information deserves weight and which should be discounted.

2.6.3 The dilution effect and the weakening of relevant cues

One of the most important psychological mechanisms in this literature is the dilution effect. Nisbett, Zukier, and Lemley (1981) provide evidence for a dilution effect in judgement. When participants received a mixture of diagnostic and nondiagnostic information, their predictions were markedly less extreme than when they received diagnostic information alone. The authors do not explain this pattern as a simple numerical averaging rule. Rather, they argue that additional individuating but nondiagnostic details reduce the perceived similarity between the target and the outcome implied by the diagnostic information. In that sense, the weaker or irrelevant details do not merely add noise. They attenuate the apparent strength of the most informative cues and thereby soften the overall judgement.

This finding is especially important because it suggests that irrelevant information does not merely add harmless background clutter. It can actively reduce the impact of relevant information. The problem is therefore not only that decision-makers waste effort on unhelpful cues. It is also possible that their final judgement may shift away from what the best available evidence would support. In settings where accuracy depends on weighing the most predictive indicators appropriately, this can have clear negative consequences.

The dilution effect is highly relevant to financial decision-making because investors are often exposed to both highly and weakly diagnostic information at the same time. Financial statements, earnings data, and cash-flow information may be presented alongside managerial narratives, corporate image signals, or other materials that are less informative for the immediate judgement task. When this occurs, investors may not simply ignore the weaker cues. They may instead allow those cues to soften or distort the impact of the stronger evidence.

This mechanism provides an important bridge between psychology and finance. It suggests that poorer judgements in financial settings may arise not only because investors lack relevant information, but because the informational environment includes additional cues that interfere with the proper use of that information. In that sense, irrelevant information can weaken judgement even when the relevant evidence is fully available.

2.6.4 Irrelevant information as extraneous cognitive load

The role of irrelevant information can also be understood through Cognitive Load Theory. In that framework, information that must be processed but does not support task completion creates unnecessary cognitive burden. Sweller's work (1988) treats such material as extraneous in the sense that it consumes limited working-memory resources without advancing understanding or performance. This perspective is useful because it explains why irrelevant information may reduce performance even when it is not misleading in any strong sense. The problem is not only that the information points in the wrong direction. The problem is also that processing it imposes a cost.

From this viewpoint, irrelevant information matters because working memory is limited and can be overloaded when too much material competes for processing. If individuals must devote part of their attention to cues that do not contribute to the task, they may have fewer resources left for the cues that actually matter. This is especially important when tasks are already demanding, because the addition of even mildly irrelevant material may push the decision-maker closer to cognitive overload.

This logic fits well with the broader argument of the present thesis. The financial decision environment studied here is not one in which participants can leisurely inspect all available information and later decide what was useful. They must process cues under time constraints and produce a judgement within a limited window. Under such conditions, irrelevant information is likely to be especially costly because it competes directly with the processing of more diagnostic financial cues.

2.6.5 Evidence from seductive details and learning research

A large body of work in educational psychology examines a closely related phenomenon through the literature on seductive details. This work asks whether interesting but unimportant information can impair learning by drawing attention away from core content. Although the context differs from financial decision-making, the underlying mechanism is highly relevant because both settings involve selective attention, limited working memory, and the need to identify what matters most.

Many studies report that seductive details reduce recall, comprehension, or transfer. Harp and Mayer (1998), Korbach et al. (2017), and Mayer et al. (2008), among others, suggest that seductive details capture attention and consume processing resources that would otherwise be used for essential information. Reder and Anderson (1980; 1982) similarly show that concise summaries can sometimes produce better learning than fuller textbook chapters, which is consistent with the idea that additional material is not always beneficial. These findings suggest that learners may perform better when non-essential details are removed rather than added.

Several mechanisms have been proposed to explain these results. One is the distraction account, in which seductive details simply draw attention away from the relevant material. Another is the disruption account, in which they make it harder for the learner to form a coherent mental representation of the core content. A third is the diversion account, in which they activate prior knowledge that is unrelated to the task and thereby push the learner toward the wrong interpretive framework. These mechanisms are not mutually exclusive. In practice, irrelevant information may distract, disrupt, and divert at the same time.

The Cognitive Theory of Multimedia Learning, proposed by Mayer (2014) provides a useful way of thinking about these effects. Meaningful learning requires learners to select relevant material, organise it into verbal and visual structures, and integrate those structures with prior knowledge. Irrelevant details can interfere with each of these steps. They may draw attention away from the core information, disrupt the building of a coherent mental model, or trigger knowledge that is not useful for the present task. Although developed in educational settings, this framework has obvious implications for investment problems. Investors also need to select, organise, and integrate information under limited capacity. If irrelevant cues pull that process away from the central evidence, performance is likely to suffer.

Eye-tracking studies reinforce this interpretation. Park, Korbach, and Brünken (2015) show that seductive details attract visual attention and are associated with poorer recall and comprehension. Chang and Choi (2014) similarly find that longer gaze durations on seductive details are linked to poorer recall, suggesting that greater attention to irrelevant material reflects deeper but misdirected processing. These findings are useful because they suggest that the negative effect of irrelevant information is not purely hypothetical. It can be observed in how attention is actually allocated during the task.

2.6.6 Mixed evidence and important moderators

At the same time, the literature does not suggest that all irrelevant information is always harmful in exactly the same way. Meta-analytic evidence shows that the effects of seductive details vary depending on features such as timing, format, learner pacing, prior knowledge, and the type of outcome being measured. Rey (2012) reports an overall detrimental effect, but also notes that the magnitude of the effect depends on contextual moderators. Sundararajan and Adesope (2020) reach a similar conclusion and show that several methodological and theoretical variables shape the strength of the effect.

These moderating factors matter because they suggest that the consequences of irrelevant information are conditional rather than automatic. For example, seductive details may be more harmful when introduced early, perceived as relevant, or when the learner has limited cognitive resources to resist distraction. Sanchez and Wiley (2006) show that learners with lower working-memory capacity are more vulnerable to seductive details, which is consistent with the idea that the ability to regulate attention is important. Bender et al. (2021) and Eitel et al. (2019) similarly find that seductive details are especially harmful when learners mistakenly regard them as relevant.

A smaller set of studies reports more positive or mixed effects. Wang et al. (2021) show that longer seductive text can sometimes improve transfer, possibly by creating a form of desirable difficulty that prompts deeper processing. Towler (2009) likewise suggests that reduced coherence may sometimes encourage more flexible understanding and better problem solving. These findings are worth acknowledging because they caution against an overly rigid conclusion that all non-essential information must always be harmful.

Even so, these exceptions do not overturn the broader implication for the present thesis. Much of the positive evidence comes from learning contexts where the goal is long-run transfer, conceptual flexibility, or strategy development rather than immediate analytical accuracy. The decision environment studied in this thesis is different. Participants must reach accurate valuations and trading judgements within a limited time. In such settings, the dominant expectation remains that irrelevant information will consume resources, divert attention, and make it harder to focus on the cues that are truly diagnostic.

2.6.7 Evidence from auditing, accounting, and finance

Research in auditing and accounting provides a more direct bridge to financial judgement because these settings also involve evaluating mixed sets of diagnostic and non-diagnostic cues. A recurring finding in this literature is that irrelevant information can weaken the influence of relevant evidence and produce the same kind of dilution effect observed in psychology.

Glover (1997) shows that auditors' judgements are diluted by non-diagnostic information, becoming less extreme and less tightly linked to the diagnostic cues. This is particularly important because the study also suggests that time pressure may reduce the dilution effect by forcing greater selectivity. Shelton (1999) likewise finds that less-experienced auditors are affected by irrelevant information, but more-experienced auditors are not, suggesting that professional expertise can provide some protection, even if it does not prevent dilution at earlier career stages.

Accounting research reaches similar conclusions. Kaplan et al. (1990) suggest that investor judgements can be influenced when financial statements are accompanied by additional impression-management material such as a president's letter. Davis, Lohse, and Kottemann (1994) show that participants given supplementary news alongside stock-price information produce less accurate forecasts while becoming more confident in their predictions. This is a particularly important finding because it shows that irrelevant information may simultaneously reduce accuracy and increase subjective certainty. Frederickson and Miller (2004) also show that investor judgements can be affected by the way additional earnings-related information is presented. Taken together, this literature suggests that more information does not necessarily improve decision quality and may instead distort the balance between confidence and accuracy.

The broader disclosure literature reinforces this concern. Annual reports and other corporate filings have become longer, more repetitive, and in some cases less readable over time. Dyer, Lang, and Stice-Lawrence (2017) document increases in length, boilerplate content, stickiness, and redundancy in 10-K filings, alongside decreases in specificity and readability. This does not mean that all additional disclosure is irrelevant. Some complexity and elaboration may be informative. However, it does suggest that part of the modern disclosure environment may burden users with material that is repetitive, weakly informative, or difficult to evaluate efficiently.

This concern is reflected in the debate over informative versus obfuscatory disclosure. Some studies suggest that longer or more detailed disclosure can convey useful information. Others argue that firms may use complexity, redundancy, or readability reduction strategically to obscure rather than clarify. In that sense, information irrelevance does not always arise accidentally. It may also be embedded in disclosure choices that make value-relevant signals harder to extract.

A particularly interesting recent literature examines managerial responses during earnings communication conferences and related question-and-answer settings. Hao et al. (2025) show that irrelevant managerial responses are associated with larger analyst forecast errors, especially when the digressions concern product-related topics. Liu, Chi, and Wang (2024) similarly find that higher semantic similarity between analyst questions and managerial answers is associated with more accurate analyst forecasts and more frequent forecast revisions. Wang, Li, and Bian (2024) extend the argument by showing that irrelevant managerial responses may even spill over to supplier firms by increasing uncertainty about customer firms' future prospects. These findings suggest that irrelevance is not simply a stylistic problem.

It can materially affect how information is interpreted and how decisions are made.

2.6.8 Irrelevant information, limited attention, and information overload

The relationship between irrelevant information, limited attention, and information overload is especially important for the present thesis. Limited attention is the broader constraint arising from the fact that cognitive resources are finite. Information overload describes one state in which those limits become especially binding. Irrelevant information fits into this framework because it absorbs attention without improving the decision maker's ability to solve the task.

This means that irrelevant information can worsen both attention scarcity and overload. First, it competes directly with relevant cues for limited processing resources. Second, it increases the total volume of material that must be screened and organised. In that sense, irrelevance can intensify the burden of an already demanding decision environment. These conditions create a demanding informational environment. A participant may not simply face more information. The participant may face more information of lower average usefulness, which makes efficient selection harder.

This also helps clarify why irrelevant information should not be treated as identical to information quantity. Quantity refers to the amount of information available. Irrelevance refers to the informational quality of at least part of that material in relation to the decision task. A high-volume information set may still be manageable if most cues are clearly relevant and well-structured. By contrast, a smaller set may be difficult if some cues are salient but non-diagnostic, because the decision-maker must spend effort deciding what to ignore. Irrelevance, therefore, represents a distinct source of cognitive demand.

2.6.9 Relevance to the present thesis

This literature provides a strong conceptual foundation, but it also leaves an important gap. Much of the existing work comes from psychology, education, auditing, and disclosure research. These studies show quite clearly that irrelevant information can divert attention, dilute judgement, and consume working-memory resources. Yet there is still relatively little evidence on how financial decision-makers cope with information irrelevance in controlled tasks that require numerical valuation and trading judgements under explicit time limits.

That gap matters because real financial environments frequently contain a mixture of relevant and irrelevant cues. Investors may have to decide quickly which information deserves weight and which does not, often under conditions where all cues appear potentially informative at first glance. In such settings, the ability to screen effectively becomes central to sound judgement.

The present thesis addresses this issue by examining information irrelevance in a controlled laboratory setting. The irrelevant data include firm characteristics such as R&D expenditure and number of employees, which may appear informative or salient but are not required for the intrinsic-value calculation or the immediate trading decision. This design makes it possible to test whether irrelevant information reduces decision quality, raises perceived mental effort, and becomes especially harmful when participants also face greater task complexity, heavier information quantity, and tighter time constraints.

In this setting, the cost of irrelevant information is likely to arise through misdirected attention rather than through sheer volume alone. When non-diagnostic cues compete with genuinely useful financial indicators, investors must devote extra effort to screening and discounting information that does not advance the task. That should make accurate judgement more difficult and the decision process more effortful, especially when the task is already numerically demanding and time-constrained.

2.7 Hypotheses

Recent research in behavioural finance and economics suggests that investors are subject to limited attention and finite processing capacity. Market participants do not always fully process corporate disclosures when announcements are released at low-attention times, such as Fridays or after trading hours, or when several firms make announcements simultaneously (DellaVigna & Pollet, 2009; Hirshleifer et al., 2009; Louis & Sun, 2010; deHaan et al., 2015). Related evidence shows that analysts' forecast timeliness and accuracy deteriorate when they must process multiple disclosures at the same time, which suggests that concurrent informational demands can reduce judgement quality (Driskill et al., 2020; Hirshleifer et al., 2019). This literature is consistent with Cognitive Load Theory, which holds that information is processed in working memory and that performance declines when task demands exceed limited processing capacity (Baddeley A., 1992; Miller, 1956; Sweller J., 1988). In settings where investors must process multiple financial cues quickly, increasing information quantity should place heavier demands on working memory, reduce the accuracy of judgement, and raise the subjective cost of processing. Accordingly, the following hypotheses are proposed.

Hypothesis 1a: Under a fixed time constraint, investor decision quality decreases as information quantity increases.

Hypothesis 1b: Under a fixed time constraint, perceived mental effort increases as information quantity increases.

Task complexity should generate a similar pattern through a related but distinct mechanism. Under a structuralist view, complexity rises when tasks contain more elements and when the relationships among those elements become more interdependent (Wood, 1986; Campbell, 1988; Bonner, 1994). In financial decision tasks, greater complexity requires more screening, coordination, and verification, which places additional strain on limited working memory. As complexity rises, decision-makers are more likely to rely on selective or simplified processing, which increases the risk that diagnostic cues will be underweighted or incorrectly combined. At the same time, the subjective effort required to complete the task should increase because more cognitive resources are needed to manage and reconcile the relevant information. This reasoning leads to the following hypotheses.

Hypothesis 2a: Under a fixed time constraint, investor decision quality decreases as task complexity increases.

Hypothesis 2b: Under a fixed time constraint, perceived mental effort increases as task complexity increases.

Irrelevant information should also impair performance because it consumes cognitive resources without improving task performance. Drawing on Cognitive Load Theory, irrelevant or non-diagnostic cues can be understood as a source of extraneous cognitive load because they occupy working-memory capacity that could otherwise be devoted to information that is genuinely useful for the decision (Sweller, 1988). Prior research on the dilution effect further suggests that when diagnostic and non-diagnostic information are presented together, individuals often fail to discount the irrelevant material fully and instead spread attention too broadly across available cues (Nisbett et al., 1981). In a financial setting, this implies that investors may give weight to salient but unhelpful details while underweighting the core indicators needed for accurate valuation and trading decisions. Irrelevant information should therefore lower decision quality and increase the effort required to filter and interpret the available cues. Taken together, these arguments lead to the following hypotheses.

Hypothesis 3a: Under a fixed time constraint, investor decision quality decreases when irrelevant information is incorporated into a financial problem.

Hypothesis 3b: Under a fixed time constraint, perceived mental effort increases when irrelevant information is incorporated into a financial problem.

Time pressure is expected to exert an additional negative effect on judgement. Although tighter deadlines can sometimes sharpen focus, the broader psychology and decision-making literature suggests that time pressure more often reduces analytical depth, narrows information search, and increases reliance on heuristics or other simplifying strategies (Kruglanski & Freund, 1983; Tversky & Kahneman, 1974; Diederich, 1997). Under greater time pressure, decision-makers have less opportunity to evaluate alternatives carefully, verify calculations, or integrate multiple cues thoroughly. This should reduce decision quality and make the task feel more effortful. In the present study, the shorter time condition is expected to create greater subjective time pressure than the longer condition. On that basis, the following hypotheses are advanced.

Hypothesis 4a: Higher time pressure reduces the investor's decision quality.

Hypothesis 4b: Higher time pressure increases the perceived mental effort.

Taken together, the literature reviewed in this chapter suggests that investor decision quality and perceived mental effort should vary systematically with information quantity, task complexity, irrelevant information, and time pressure. These hypotheses provide the theoretical foundation for the empirical analysis that follows. The next chapter explains how these constructs are operationalised and tested through a controlled experimental design.

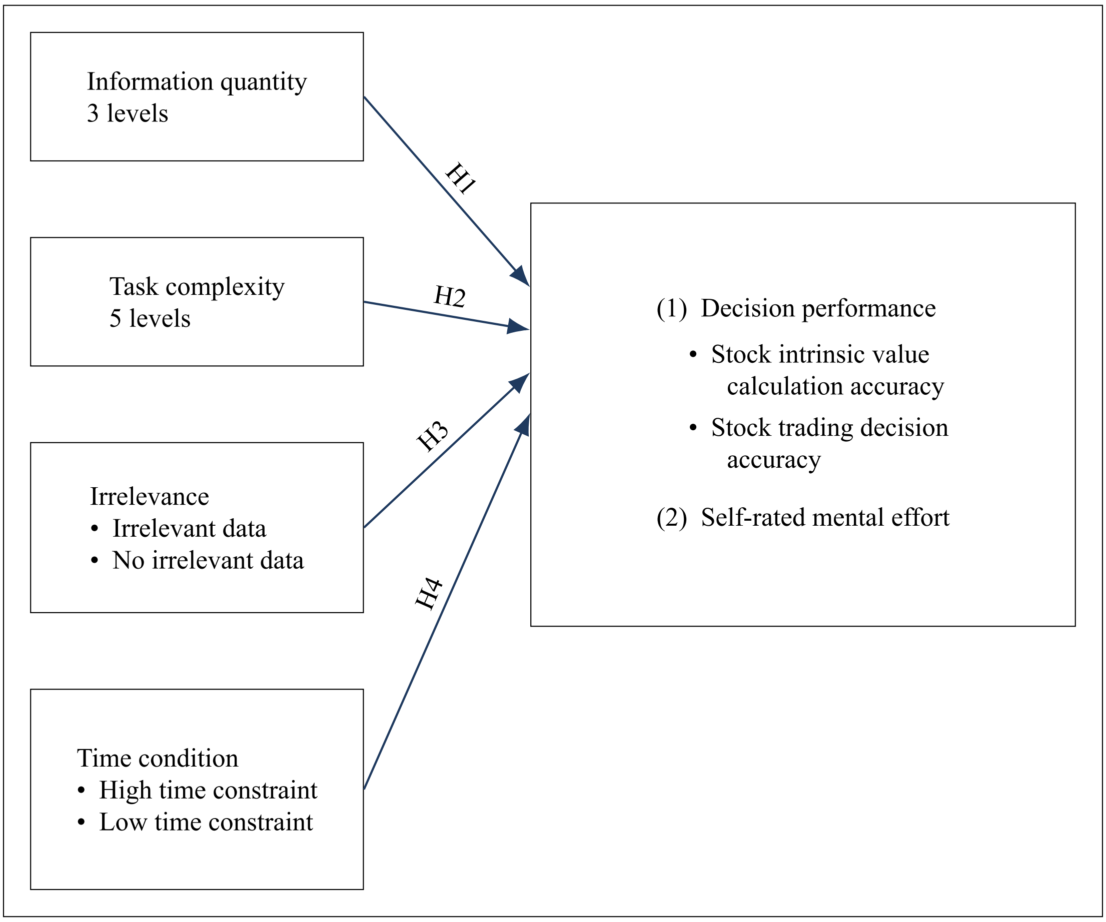

Figure 2.1: Research hypothesis

Chapter 3

Methodology

Building on the theoretical framework and hypotheses developed in Chapter 2, this chapter outlines the methodology used to examine how information quantity, task complexity, irrelevant data, and time constraint affect investor decision quality and self-rated mental effort. The chapter describes the experimental design, task construction, measures, procedure, participants, and pilot testing.

3.1 Overview and hypotheses

The hypotheses developed in Chapter 2 are tested through a laboratory stock-trading experiment conducted across three related studies. The design combines within-participant variation in task complexity with between-participant variation in information quantity, irrelevant data, and time constraint. The following section summarises the research design and the mapping between the core variables and hypotheses.

Table 3.1: Research model and hypotheses.

Dependent variables	Independent variables	Levels	Linked hypotheses
Intrinsic-value calculation accuracy Trading-decision accuracy Self-rated mental effort	Information quantity	Three levels	H1a and H1b
	Task complexity	Five levels	H2a and H2b
	Irrelevant data	Present or absent	H3a and H3b
	Time constraint	3 minutes or 5 minutes per question	H4a and H4b

3.2 Experimental design

The research consists of three related studies and, in total, nine experimental conditions, which are shown in Tables 3.2 and 3.3. In all studies, task complexity is varied within participants, so each participant completes five question sets that correspond to the five levels of overall task complexity. Information quantity is varied between participants across three levels, low, medium, and high. Study 2 introduces irrelevant data, and Study 3 introduces a more relaxed time constraint.

All three studies use a 5 by 3 factorial design. Task complexity has five levels, and information quantity has three levels. In the lowest information-quantity condition, each task includes two companies. In the medium and high information-quantity conditions, each task includes four and six companies respectively. The number of companies stops at six because the pilot work suggested that a larger set would overwhelm participants even under the more relaxed time condition. To identify overload effects cleanly, the information presented in the lower information-quantity condition is a subset of that in the higher information-quantity conditions.

Consistent with Iselin (1988) and Shields (1983), information quantity is defined here as a change in the amount of structurally equivalent information that must be processed to reach the same type of decision. This approach differs from designs in which additional information is also more informative or qualitatively different. Here, the algorithm, information types, and response format are held constant within a given complexity level. Only the number of like cues changes. That design helps remove the usual information-value confound.

Table 3.2: Number of companies in each level of information quantity.

Level of information quantity	**Companies per task**
1	2
2	4
3	6

Table 3.3: Description of each condition.

Condition	**Task complexity**	**Information quantity**	**Irrelevant data**	**Time constraint**
1	Levels 1–5	1	No	3 minutes per question
2	Levels 1–5	2	No	3 minutes per question
3	Levels 1–5	3	No	3 minutes per question
4	Levels 1–5	1	Yes	3 minutes per question
5	Levels 1–5	2	Yes	3 minutes per question
6	Levels 1–5	3	Yes	3 minutes per question
7	Levels 1–5	1	No	5 minutes per question
8	Levels 1–5	2	No	5 minutes per question
9	Levels 1–5	3	No	5 minutes per question

A related concern is task confounding. Following Iselin (1988) and the task-taxonomy logic discussed by Fleishman (1982), a confound would arise if higher-load conditions changed the task class itself. That is unlikely in the present design because the higher information-quantity versions use the same valuation algorithm, the same information types, and the same response format as the lower versions. The higher-load task simply adds more companies of the same type.

Study 2 adds irrelevant data, namely number of employees and research and development expenditure, to Conditions 4, 5, and 6. Following Wyatt (2008), these cues are not treated as reliable indicators of firm value in the present setting and are not required for the intrinsic-value calculation or the trading decision. Apart from this addition, Conditions 4, 5, and 6 match Conditions 1, 2, and 3 respectively. All six of these conditions use the tighter time constraint of three minutes per question.

Study 3 varies time constraint. Participants in Conditions 7, 8, and 9 receive the same task materials as participants in Conditions 1, 2, and 3 respectively, but they are given five minutes rather than three minutes for each question. This design allows the effect of time constraint to be examined by comparing the three-minute and five-minute versions of the same information-quantity conditions.

3.3 Task construction and manipulations

3.3.1 Task type and task complexity

The tasks were drawn from the finance domain so that prior exposure to the underlying valuation methods could be embedded in participants' coursework. This choice increases the likelihood that the student pool had the domain knowledge needed to engage with the tasks meaningfully. The experiment uses four underlying question types, which are then combined to form five overall levels of task complexity at the question-set level.

The classification follows Wood's (1986) framework. In this framework, task complexity has two main aspects. Component complexity refers to the number of cues and acts required to perform the task. Coordinative complexity refers to the extent to which later steps depend on earlier steps and the degree of coordination needed across acts. Using Wood's notation, component complexity can be expressed as:

$$\mathrm{TC}_1 = \sum_{j=1}^{j=p} \sum_{i=1}^{i=n} W_{ij}$$

where $n =$ number of distinct acts in subtask j, $W_{ij} =$ number of information cues to be processed in the performance of the i^{th} act of the j^{th} subtask, $p =$ number of subtasks in the task, and $\mathrm{TC}_1 =$ component complexity.

In the present study, the first type of underlying task requires participants to examine three cues and perform one calculation. The second requires five cues and two calculations. The third requires seven cues and three calculations. The fourth also requires seven cues, but adds a further calculation step and therefore greater coordination across intermediate values. This progression increases both the amount of information that must be processed and the degree to which later steps depend on the earlier ones. These are shown in Table 3.4.

The number of cues per company ranges from three to seven. This range was chosen with working-memory limits in mind. Miller (1956) suggests a broad capacity range of about seven plus or minus two items, while later work often argues for a smaller effective range. Keeping the cue set within this range reduces the risk that performance differences are driven merely by immediate memory overload rather than by the intended manipulation of task complexity.

Table 3.5 shows that the five experimental complexity levels are based on combinations of these four underlying task types. The first question set combines one level 1 task and one level 2 task, for a total of eight cues and three calculation steps. The second combines level 1 and level 3, for a total of ten cues and four calculation steps. The logic continues in the same way, so that the fifth question set combines level 3 and level 4 and therefore imposes the highest overall complexity. This structure creates a graded increase in overall demand while keeping the task domain constant.

The experiment tasks require participants to calculate the intrinsic value of a stock using well-known valuation models, including the price-to-earnings ratio, the Gordon growth model, and the capital asset pricing model. Bancel and Mittoo (2014) report that these models are widely used by finance practitioners in Europe. The tasks can therefore be seen as simplified but recognisable versions of structured financial decisions. All participants were required to have studied these models during their degree.

Table 3.4: Task complexity definition.

	Level 1	**Level 2**	**Level 3**	**Level 4**
Earnings per share (EPS)	2.00	2.50	2.00	2.00
Company P/E ratio	9.80	–	–	–
Earnings retention ratio (b)	–	70.00%	70.00%	68.00%
Sustainable growth rate (g)	–	4.00%	5.00%	–
Return on equity (ROE)	–	–	–	7.35%
Required rate of return (R)	–	9.00%	–	–
Systematic risk (β)	–	–	0.75	0.71
Risk-free rate (Rf)	–	–	4.00%	4.00%
Expected market return (Rm)	–	–	12.00%	11.00%
Current market price	17.64	15.00	12.00	16.00
Calculation method	1. Calculate $P = (P/E) \times EPS$	1. Calculate $D = E \times (1 - b)$ 2. Calculate $P = D/(R - g)$	1. Calculate $R = Rf + \beta \times (Rm - Rf)$ 2. Calculate $D = E \times (1 - b)$ 3. Calculate $P = D/(R - g)$	1. Calculate $g = b \times ROE$ 2. Calculate $R = Rf + \beta \times (Rm - Rf)$ 3. Calculate $D = E \times (1 - b)$ 4. Calculate $P = D/(R - g)$
Number of cues	3	5	7	7
Number of calculation steps	1	2	3	4

Table 3.5: Number of cues in each level of complexity.

Level of complexity	Combination of questions	Total cues	Total calculation steps
1	L1 and L2	8	3
2	L1 and L3	10	4
3	L1 and L4	10	5
4	L2 and L4	12	6
5	L3 and L4	14	7

3.3.2 Information quantity

Information quantity is manipulated through the number of companies that participants must evaluate within each question. Level 1 presents two companies, Level 2 presents four companies, and Level 3 presents six companies. Within a given complexity level, the same valuation logic applies in each information-quantity condition. The higher-quantity versions therefore require participants to process more of the same kind of information rather than a different kind of task.

This design is important for interpretation. Because the lower information-quantity condition is a subset of the higher conditions, any systematic deterioration in performance can more plausibly be attributed to the increased amount of information that must be processed. The manipulation therefore targets quantity rather than informational quality.

3.3.3 Irrelevant data

Irrelevant data are introduced in Study 2 through two additional cues, number of employees and research and development expenditure. The additional variables used in Study 2 should be understood as task-irrelevant rather than economically irrelevant in a general sense. Prior research shows that R&D expenditure can contain information relevant to firm valuation and future returns (Chan et al., 2001), while workforce characteristics and technical human capital can also be associated with firm valuation and subsequent performance (Fedyk & Hodson, 2023). In the present experiment, however, these variables are not inputs into the specified valuation models and therefore provide no diagnostic information for calculating the correct intrinsic value or trading decision. The manipulation is therefore intended to capture the processing cost of non-diagnostic information within the specific experimental task, rather than to imply that such information has no broader economic relevance.

3.3.4 Time constraint

Time constraint is manipulated at two levels, three minutes and five minutes per question. The three-minute condition represents the tighter time window and is used in Studies 1 and 2. The five-minute condition is used in Study 3 and provides a more relaxed but still finite period for processing.

This manipulation follows the pilot findings and is broadly consistent with prior experimental work that compares more severe and more moderate timing conditions, such as Snowball (1980). In the present design, the comparison between three minutes and five minutes allows the effect of time constraint to be examined without changing the information set or the response format.

3.3.5 Data presentation format

Financial information is presented in tabular form. This choice is consistent with cognitive-fit theory, which suggests that symbolic tasks such as calculation are better supported by symbolic representations than by spatial displays (Bettman & Kakkar, 1977; DeSanctis, 1984; Vessey, 1991). A table format therefore fits the analytical demands of the present tasks.

The hypothetical stock values are standardised within a relatively low price range, from $10 to $20. This range is used only for the experimental task and does not affect participant compensation, which is paid separately in Vietnamese Dong. A low price range also makes the pricing gap easier to evaluate. Consistent with Kumar and Lee (2006), low-priced stocks are familiar to retail investors, and evidence from numerical cognition suggests that people judge absolute differences more easily with smaller magnitudes (Dehaene et al., 2008; Hyde & Spelke, 2009). For each company, the hypothetical market price is set to be 10% above, 10% below, or equal to the intrinsic value. That range is designed to make the pricing gap clear while preserving the focus on information processing rather than perceptual ambiguity.

3.4 Measures

3.4.1 Intrinsic-value calculation accuracy

Intrinsic-value calculation accuracy captures participants' ability to apply the relevant valuation model correctly to the information provided in each task. This outcome reflects the quality of participants' analytical processing because it depends on identifying the relevant cues, selecting the correct formula, and carrying out the required calculation steps accurately.

3.4.2 Trading-decision accuracy

Trading-decision accuracy captures whether participants choose the appropriate action, buy, hold, or sell, after comparing their calculated intrinsic value with the hypothetical market price. This outcome reflects the quality of the final judgement that follows the calculation stage. Analysing trading-decision accuracy alongside intrinsic-value calculation accuracy makes it possible to distinguish errors in computation from errors in the final decision.

3.4.3 Self-rated mental effort

This study measures self-rated mental effort as the main subjective indicator of the cognitive burden imposed by each task. The measure is grounded in cognitive load theory, which treats task demands as pressures on limited working-memory resources. The present study adopts the more recent distinction between intrinsic and extraneous cognitive load because it offers a parsimonious way to think about how task characteristics create mental demands.

Cognitive-load research uses both objective and subjective measures. Objective approaches, such as dual-task methods or physiological indicators, can be informative but are more intrusive and less practical in the present classroom-based setting. They are also unnecessary for the present purpose, which is to capture participants' experienced mental burden immediately after each task.

Accordingly, the study uses Paas's nine-point mental-effort scale, adapted from Bratfisch, Borg, and Dornic (1972) and Paas (1992). After each question, participants indicate how much mental effort they invested on a symmetrical scale ranging from very, very low mental effort to very, very high mental effort. This instrument is widely used, simple to administer, and well suited to repeated task-level ratings.

An alternative would have been the NASA Task Load Index developed by Hart and Staveland (1988). That instrument covers several workload dimensions, including mental demand, temporal demand, performance, and frustration. It was not adopted here because the present research focuses specifically on mental effort rather than on a broader multidimensional notion of workload. Its greater length would also have interrupted the flow of the experiment.

In this study, participants report their mental effort after each question, and the average of those ratings is used as the subjective outcome measure. Higher values indicate that the participant experienced the task as more effortful.

3.5 Control variables

In addition to the stock-trading game, the study includes a questionnaire that measures participant characteristics which may influence performance or perceived effort independently of the experimental manipulations. These variables are included to reduce the risk that observed differences in outcomes reflect pre-existing differences between participants rather than the effects of information quantity, task complexity, irrelevant data, or time constraint.

3.5.1 Demographics

Age and gender are included as demographic controls. Prior work suggests that age may be related to financial decision quality, although the direction is not always consistent across samples and settings (Boyle et al., 2012; Eberhardt et al., 2019; Gamble et al., 2015). Gender is included because prior research in psychology and behavioural finance suggests that men and women may differ in processing style, confidence, and risk-taking behaviour, even when overall cognitive ability does not differ systematically (Barber & Odean, 2001; Cahill, 2006; Charness & Gneezy, 2012; Eckel & Grossman, 2002; Halpern, 2012; Hyde J. S., 2005). Including these variables helps ensure that the estimated treatment effects are not driven by differences in participant composition.

3.5.2 Financial education and financial literacy

Financial education and financial literacy are included because they may influence how efficiently participants interpret valuation inputs and apply financial concepts. Participants with stronger training are likely to comprehend the task more quickly and may therefore perform better or experience lower effort under the same experimental condition (Lusardi & Mitchell, 2014; Van Rooij et al., 2011). Financial literacy is measured with a five-item multiple-choice quiz adapted from Xiao and O'Neill (2016).

3.5.3 Risk aversion

Risk aversion is controlled for because it may shape how cautiously participants approach financial judgement under uncertainty. More risk-averse individuals may devote extra attention to checking calculations and avoiding mistakes, which could affect both decision quality and perceived effort (Boyle et al., 2012; Kahneman & Tversky, 2013). Following Van Rooij et al. (2011) and Jiang et al. (2024), risk aversion is measured using three hypothetical job-choice scenarios in which respondents choose between a safe job and a risky job. The risky option becomes progressively less attractive across the three scenarios, so acceptance of the risky job indicates greater risk tolerance.

3.5.4 Stock-trading knowledge and experience

Stock-trading knowledge and prior market experience are included as controls because recent research suggests that both can influence financial judgement and investment behaviour. Investment experience shapes stock-investment behaviour through risk perception, and investor overconfidence tends to decline with greater market experience (Li et al., 2023; Bernile et al., 2025). Related work also suggests that financial knowledge is associated with differences in risk-related decision-making, while finance-related expertise can alter behaviour in experimental financial contexts (Huber et al., 2025). In this setting, participants with greater market familiarity may process valuation inputs more efficiently and may be less likely to experience the task as equally demanding as less experienced participants. Controlling for these characteristics therefore helps isolate the effects of the experimental manipulations from pre-existing differences in financial capability and market exposure.

3.5.5 Personality traits

The study also controls for the Big Five personality traits, Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. Recent work suggests that personality may influence financial decision-making and the way individuals manage attention and cognitive demands (Ackerman & Heggestad, 1997; Aschwanden et al., 2020; Bucciol & Zarri, 2017; Firth et al., 2023; Eysenck M. W. et al., 2007; Jiang et al., 2024). For example, higher Neuroticism may be associated with greater susceptibility to stress, whereas higher Conscientiousness may support more organised task management.

Personality is measured using the 20-item SAPA Personality Inventory (Condon & Revelle., 2015; Jiang et al., 2024). Items are presented in random order, and respondents rate how accurately each statement describes them on a six-point scale from very inaccurate to very accurate. Each Big Five score is computed as the equal-weighted mean of the four items mapped to that trait.

3.6 Experimental procedure

The study combines a questionnaire with an experimental stock-trading game delivered through the Qualtrics platform. Each session had two broad parts. Participants first completed the trading game, which is the main experimental component, and then completed the questionnaire covering demographics and individual-difference measures. At the start of the experiment, participants were informed about the overall flow, shown in Figure 3.1.

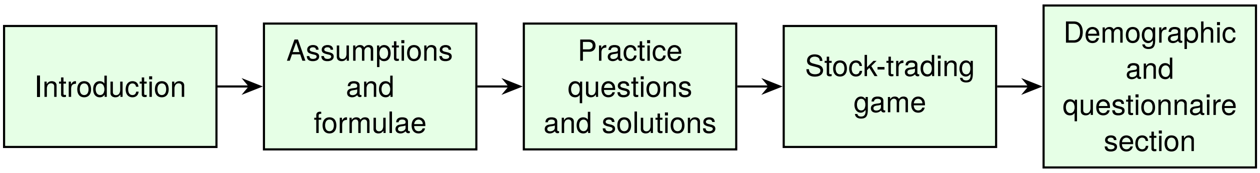

Figure 3.1: Survey flow.

3.6.1 Pre-experiment setup

The experiment was conducted in Vietnamese, so participants completed the tasks in their native language. Students were notified in advance during their regularly scheduled class and were asked to bring a laptop if they wished to participate. The lecturer allocated one hour of class time for the session. Participants completed the experiment on their own laptops in the classroom, with each student seated at least one metre away from others.

At the beginning of the session, participants were instructed to turn off mobile messaging applications on their laptops and to silence their phones. I remained in the classroom throughout the session to monitor the process and answer procedural questions. Before beginning, participants were given three minutes to read the Participant Information Sheet in Appendix B2 and ask any questions before signing the Consent Form in Appendix C2.

3.6.2 Practice phase

The experiment begins with an introduction, followed by a formula sheet, practice questions, and worked solutions. The practice phase includes four companies that correspond to the four underlying task types. There is no time limit for the practice questions. This phase is intended to ensure that participants understand the task structure, the valuation formulae, and the response format before the timed game begins.

Participants were instructed to enter numerical answers to a maximum of two decimal places before moving to the next page. They were also told how to interpret the relationship between a stock's intrinsic value and its hypothetical market price. To allow for rounding differences, participants were instructed to treat the intrinsic value and market price as effectively equal and choose to hold when the difference was less than \$0.5. If the intrinsic value exceeded the market price by at least \$0.5, the stock was treated as undervalued, and the correct response was to buy. If the intrinsic value was at least \$0.5 below the market price, the correct response was to sell.

This rounding rule does not alter the correctness of the trading task because the hypothetical market price is always set to be either 10% above, 10% below, or equal to the intrinsic value. Given the \$10 to \$20 price range, those gaps are always at least \$1. The \$0.5 tolerance therefore protects against trivial rounding differences without changing the correct decision rule.

After completing the practice questions, participants moved to a page that displayed the worked solutions. Only after reviewing those solutions did they proceed to the timed stock-trading game.

3.6.3 Randomisation

Participants were randomly assigned to one of the nine experimental conditions shown in Table 3.3. Within each condition, the order of the five complexity levels was also randomised. For example, one participant might see the complexity levels in the order 3, 1, 5, 2, and 4, while another might see 4, 3, 2, 5, and 1.

Randomisation serves several purposes. It helps minimise systematic practice, fatigue, and learning effects, reduces the risk that responses are shaped by a fixed item order, and makes it more difficult for participants to exchange answers. The randomisation was implemented using the Qualtrics question-randomisation function, and the order presented to participants was checked to confirm that the sequence varied across respondents.

3.6.4 Game phase

In the stock-trading game, participants completed five timed questions, one for each level of overall task complexity. Depending on the assigned condition, each question included two, four, or six companies. For each company, participants used the provided data and valuation formulae to calculate intrinsic value, compared that value with the hypothetical market price, and then chose buy, hold, or sell.

The structure of the game questions matched the structure of the practice questions, but the game questions were timed. Conditions in Studies 1 and 2 used a three-minute time limit per question, whereas the matched conditions in Study 3 used a five-minute time limit. After each question, participants reported their mental effort on the nine-point scale. The average of these ratings serves as the self-rated mental-effort outcome.

3.6.5 Post-game questionnaire

After the stock-trading game, participants completed the questionnaire section covering financial literacy, personality traits, demographic information, risk aversion, and related background characteristics. Once a participant had finished the full experiment, I checked the completion screen and provided the participation gift card. The complete instructions and screenshots of the experiment are included in Appendices G1 and G2.

3.7 Participants and sample size

3.7.1 Participants

Approximately 500 third- and fourth-year undergraduate students majoring in finance, accounting, or economics participated in the experiment. They were recruited from the University of Economics - The University of Da Nang, Foreign Trade University, and the Academy of Finance in Vietnam. These institutions have broadly similar entry requirements, so participants are likely to have comparable academic preparation.

All participants had already completed finance courses covering asset pricing and stock valuation, including the three valuation models used in the experiment. This background makes them suitable for the present tasks because the experiment is not testing whether participants have ever seen the models before. Rather, it examines how well they process structured financial information under different task demands.

To encourage careful participation, each participant received a 50 000 Vietnamese Dong (VND) gift card for participating and the opportunity to enter a random drawing for a 300,000 VND gift card. Given that the average hourly wage for a casual student job is about 20,000 VND, this incentive was intended to encourage sincere and attentive participation.

3.7.2 Justification for the student sample

The use of students is appropriate for the present research question because the study focuses on attention, information processing, calculation, and judgement under structured experimental conditions. Prior work in experimental economics, accounting, and finance suggests that student participants can be suitable proxies when the aim is to study general behavioural mechanisms rather than institution-specific professional expertise (Ashton & Kramer., 1980; Hoffmann & Post., 2016; Libby et al., 2002). A number of experimental finance studies also use student samples for this reason (Cueva et al., 2019; Frydman et al., 2014; Kirchler et al., 2018).

That justification is especially relevant here because all participants had prior exposure to the valuation models used in the task. The design therefore does not rely on naive participants guessing unfamiliar concepts. Instead, it examines how changes in information quantity, task complexity, irrelevant data, and time constraint affect performance once the basic domain knowledge is in place.

3.7.3 Sample size and statistical power

The achieved sample size is substantially larger than the minimum implied by conventional power calculations for a design of this kind. Using G*Power with the repeated-measures ANOVA (Cohen J., 2013), between-factors option, a medium effect size of $f = 0.25$, alpha = 0.05, power = 0.80 to 0.90, nine groups, five repeated measurements, and an assumed correlation of 0.5 among repeated measures suggests a total sample of roughly 108 to 135 participants. My study recruited nearly 500 participants, with at least 50 students in each condition.

3.8 Pilot study

Pilot tests were conducted to assess the suitability of the materials and the feasibility of the experimental procedure. First, a group of finance lecturers at the University of Economics - The University of Da Nang reviewed the information cues used in the tasks. They agreed that number of employees and research and development expenditure were irrelevant to the valuation models used in the experiment, whereas the remaining financial data were necessary inputs for stock valuation.

Second, 45 students were recruited to evaluate the overall design. These pilots suggested that students who had studied the three valuation models did not experience difficulty with the basic logic of the tasks. However, when the number of companies per question exceeded six, most participants struggled to complete the task comfortably. This finding led to the decision to retain three information-quantity levels and to cap the number of companies at six per question.

The pilot work also informed the time-constraint manipulation. An initial comparison was made between a three-minute condition and a no-time-limit condition. The no-time-limit version proved impractical because some students took more than one hour to complete the game, and performance became uniformly very high across task conditions. That pattern reduced meaningful variation in the outcomes and made the sessions difficult to manage within a classroom setting.

On the basis of these observations, the no-time-limit condition was dropped and replaced with a five-minute time limit per question. The five-minute condition remains more relaxed than the three-minute condition, but it still preserves time as a meaningful task constraint. The final design therefore uses three minutes as the tighter condition and five minutes as the more relaxed condition.

Overall, the final methodology was designed to vary cognitive demands in a controlled and transparent way while keeping the task domain, response format, and underlying valuation logic constant across conditions. This structure allows the later analyses to attribute changes in performance and self-rated mental effort more clearly to the intended experimental manipulations.

Chapter 4

The impact of information quantity and task complexity on decision quality and mental effort

4.1 Study 1 motivation and design

Study 1 is motivated by a simple capacity question. In many financial settings, decision makers face problems that become harder along two dimensions. The task itself can become more complex, requiring more element interactivity and more integration across cues. At the same time, the information set can expand, forcing the decision maker to track and combine more relevant inputs. If cognitive capacity is limited, both dimensions should reduce decision quality, and their joint increase may be especially damaging.

The theoretical motivation draws on Cognitive Load Theory and related capacity-based accounts. Cognitive Load Theory predicts that performance deteriorates once intrinsic task demands exceed working-memory capacity, even when individuals invest more effort. In a valuation setting, higher information quantity increases the number of relevant figures that must be encoded and maintained, while higher task complexity increases the amount of mental manipulation required to integrate those figures into a final intrinsic value and, subsequently, a trading decision. This logic motivates the Study 1 hypotheses that information quantity reduces accuracy and increases perceived effort, and that task complexity likewise reduces accuracy and increases perceived effort.

The design implements this test using a mixed structure across Conditions 1 to 3. Information quantity varies between participants across three levels, operationalised by the number of companies per question, with Condition 1 as low load, Condition 2 as medium load, and Condition 3 as high load. Task complexity varies within participant across five levels. The outcomes are intrinsic value calculation accuracy, trading decision accuracy, and self-rated mental effort on a 1 to 9 scale. The Study 1 sample comprises 166 students, with more than 50 participants per condition.

The analysis proceeds from descriptive comparisons to regression specifications that exploit the repeated observations across complexity levels. The descriptive section first checks balance across the three information-quantity conditions and summarises the raw outcome patterns across task complexity and information quantity. The regression models then estimate the main effects of task complexity and information quantity and test whether they interact, using centred trend coding, session fixed effects, and standard errors clustered by participant. This framework also supports marginal-effect calculations that translate the interaction coefficient into interpretable changes in the complexity gradient across information conditions, and vice versa.

4.2 Descriptive analysis

4.2.1 Balance and correlations

An analysis of individual demographic data was conducted to verify the comparability of the experimental groups for between-group comparisons. Conditions 1, 2, and 3 are used to examine the impact of information quantity and task complexity on mental effort and decision quality. A total of 166 students participated across the three conditions, with more than 50 in each. The descriptive statistics are reported in Table 4.1. All participants in these conditions were aged 18-24, with approximately 70% female. Most students reported that a portion of their education was devoted to finance. While most of these participants have little investment experience, the majority score more than 60% on the financial literacy test. Regarding risk appetite, 28% never choose the risky option, indicating a very high level of risk aversion. Of the rest, 29% select the risky job in question 1[1], 27% in question 2, and 16% in question 3, signalling progressively greater risk tolerance. Table 4.1 presents summary statistics for the participants' characteristics in these conditions. In total, there are no significant differences across three treatments with respect to gender, age, financial education, investment experience, and risk aversion. However, the financial literacy scores differ significantly between Condition 1 and Condition 2, and between Condition 1 and Condition 3. With regard to the Big Five personality traits, only Neuroticism shows significant differences between Conditions 1 and 2 and between 1 and 3. These covariates will be included in the regression models.

Table 4.2 presents the Pearson correlation matrix of the participant characteristics. The correlations show that being female is correlated with higher risk aversion and lower investment experience. Although the Big Five traits are intended to reflect distinct dimensions of personality, their observed scores typically show modest intercorrelations. For example, people who are more agreeable tend to be more open and conscientious, consistent with findings by Jiang et al. (2024).

4.2.2 Descriptive outcome patterns

With baseline characteristics summarised, I next describe the raw performance patterns across the experimental conditions. Figure 4.1 presents the mean percentage of correct Intrinsic Value (IV) calculations across task complexity (levels 1-5) and information quantity (Condition 1 (C1): two companies/question; Condition 2 (C2): four; Condition 3 (C3): six). The graph shows that the average accuracy of stock intrinsic value calculation declines as task complexity increases across all information levels; however, this decline is strongly moderated by the quantity of information.

With two companies per question in Condition 1, average accuracy begins at a very high level at task

[1] Later items represent progressively higher risk exposure.

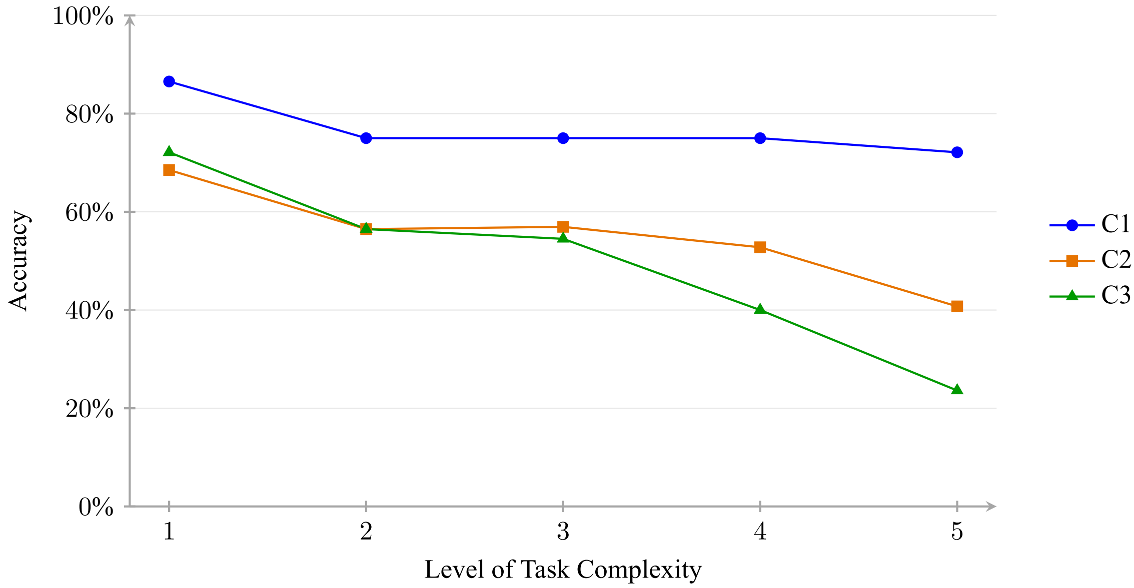

Figure 4.1: Intrinsic Value Calculation accuracy (%)

complexity level 1 (86.54%) and remains remarkably robust as complexity increases, stabilising around three-quarters correct through complexity levels 2-4 and staying above 70% even at the highest level of task complexity. In short, mean performance in Condition 1 appears relatively resilient as complexity increases, suggesting that when information load is low, task complexity may not substantially impair outcomes.

Under Condition 2 (four companies per question), average accuracy falls below the Condition 1 benchmark and declines overall as task complexity increases. The slight increase from complexity level 2 to 3 (56.48% to 56.94%) is minimal; accuracy then drops to 52.78% at level 4 and further to 40.74% at level 5. Compared to Condition 1, the decline is steeper, and the terminal level is substantially lower (level 5: 40.74% vs 72.12%).

Under the highest information load (six companies/question) in Condition 3, average accuracy begins in the low-70s at complexity level 1, but then falls most sharply with increasing complexity. The descent is especially pronounced from complexity level 3 to 4, and again from 4 to 5, where performance reaches 23.61%, the lowest endpoint across all three information conditions. This profile suggests that high information load becomes increasingly detrimental as tasks get more complex.

Regarding the effect of information quantity, at every complexity level, Condition 1 (the lowest information load) outperforms both higher information load conditions, and the size of this advantage grows with complexity. However, the magnitude of the information load effect depends on the level of task complexity. At a low task complexity level, higher information load conditions already underperform the lean baseline. As complexity increases, this disadvantage becomes more pronounced. Visually, the Condition 1 series remains high and essentially flat, Condition 2 shows a progressive decline, and Condition 3 declines most steeply, yielding increasing vertical separation between the three series with each step up in task complexity.

I next examine whether the same complexity-by-information pattern carries through to the final trading decision. Figure 4.2 presents the mean percentage of correct trading decisions as a function of task complexity and information quantity. Similar to the accuracy of intrinsic value calculations, trading decision performance is highest under Condition 1 and declines as both task complexity and information quantity increase. At the lowest level of task complexity, average accuracy reaches 88.46% under Condition 1 and is markedly lower under the higher information quantity levels (68.52% with 4 companies and 59.17% with 6 companies), indicating that a higher information load is detrimental, even for the simplest tasks.

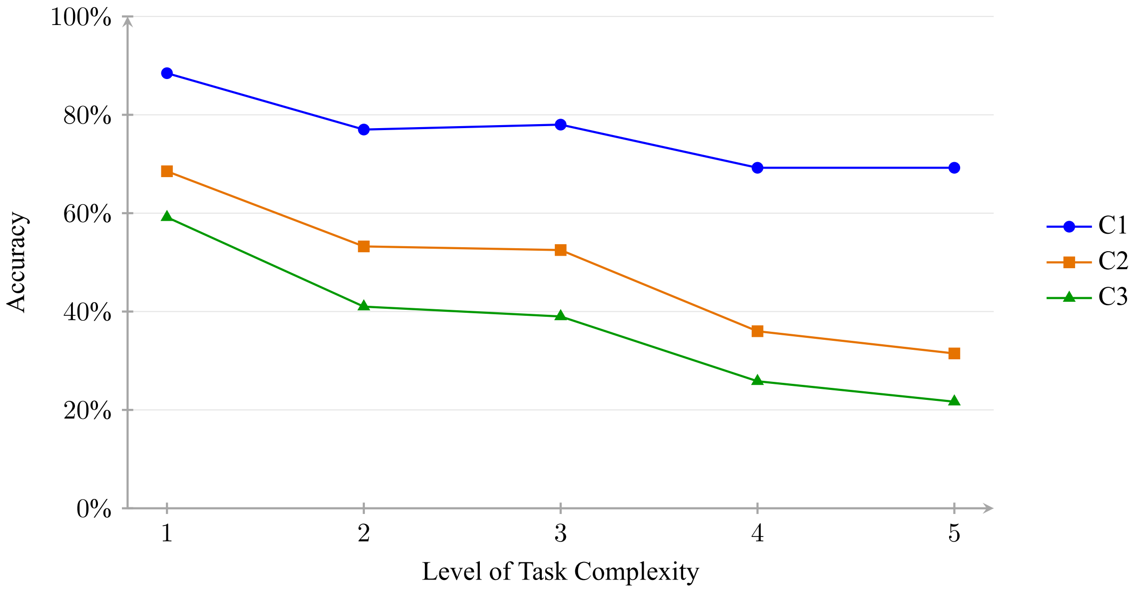

Figure 4.2: Trading decision accuracy (%)

As task complexity increases, all three conditions exhibit decreasing accuracy, but the trajectories differ. In Condition 1, performance remains comparatively robust, dipping to the high 60s at complexity levels 4 and 5 (69.23% in both cases). Under Condition 2, the average accuracy follows a steady downward slope, decreasing from 53.24% at complexity level 2 to 31.48% at level 5. Under Condition 3, the decline is steeper still, reaching 25.83% at complexity level 4 and 21.67% at level 5. Within each task complexity level, the ordering Condition 1 $>$ Condition 2 $>$ Condition 3 holds consistently, and the gaps widen as tasks become harder. In general, the results indicate a strong complexity effect on trading accuracy and a systematic, complexity-dependent penalty associated with greater information quantity. Lower information load supports more accurate trading decisions, whereas additional information increasingly undermines accuracy as problem complexity increases.

In general, participants' performance varies systematically with task complexity and the quantity of information across the two measures of decision quality (intrinsic value calculation and trading decision outcomes). At a low level of information quantity, average accuracy is very high, particularly at the lowest level of task complexity (IV calculation: 86.54%, trading decision: 88.46%). It remains robust as complexity increases, stabilising at around 75% correct for intrinsic value calculation across complexity levels 2-4 and in the high 60s for trading decisions at levels 4-5. In contrast, when there are four and especially six companies per question, average accuracy starts lower and declines steadily with increasing complexity. At every complexity level, the ordering Condition 1 $>$ Condition 2 $>$ Condition 3 holds for both decision quality measures, and the gaps widen with complexity. Taken together, the figures indicate a strong complexity effect and a complexity-dependent penalty of higher information quantity.

A low information load appears to buffer participants against rising task demands, supporting the accurate computation of intrinsic value and, correspondingly, more accurate trading decisions. In contrast, a high information load becomes increasingly detrimental as the problem becomes more complex, consistent with limited-capacity theory.

Figure 4.3 presents the mean scores of self-rated mental effort for participants in Conditions 1, 2, and 3. Participants rate their perceived workload on a 9-point Likert scale, ranging from 1 to 9. The graph shows that self-rated mental effort increases with task complexity at all information quantity levels.

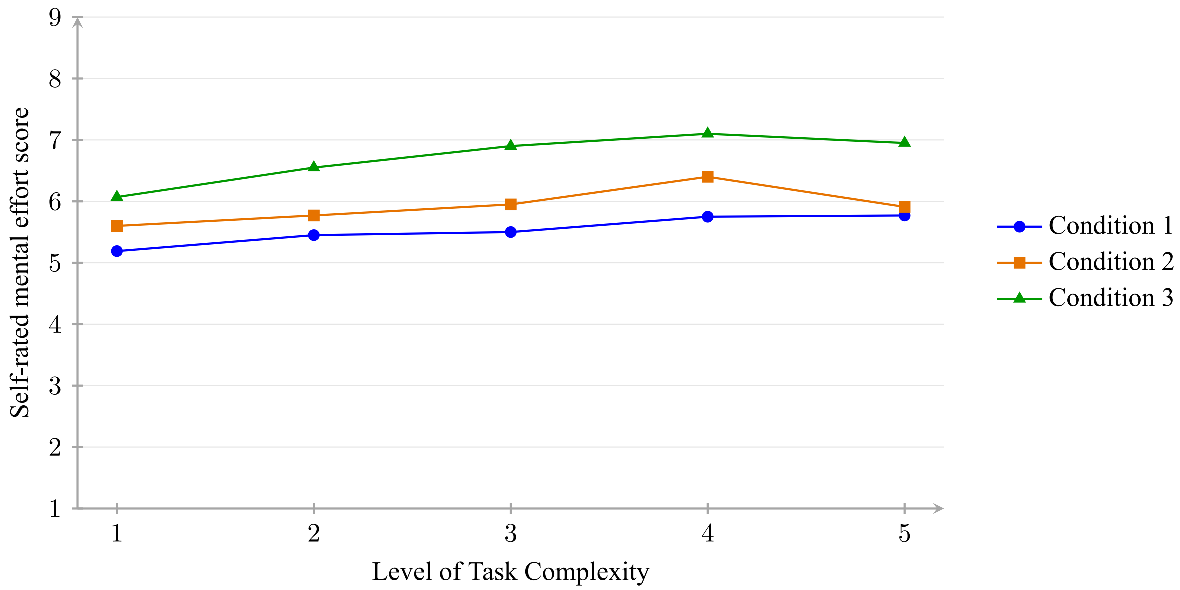

Figure 4.3: Self-rated mental effort

In Condition 1, the mean score progresses from 5.19 at task complexity level 1 to 5.77 at level 5 with small, steady steps. With four companies per question in Condition 2, perceived effort rises from 5.60 to a peak of 6.40 at level 4, then slightly eases to 5.91 at level 5. At the highest information load, ratings are highest at every step and increase most with complexity, peaking at around 7.10 at level 4 before a slight softening at level 5 (6.95). For each complexity level, average perceived effort is lowest under Condition 1, higher under Condition 2, and highest under Condition 3 (e.g., level 1: $5.19 < 5.60 < 6.07$; level 4: $5.75 < 6.40 < 7.10$). These patterns suggest a complexity-dependent information effect. As tasks become harder, additional information load likely increases perceived effort, with the largest differences between conditions evident around levels 3-4.

Although Figures 4.1-4.3 offer a clear initial snapshot of how accuracy and perceived effort vary with task complexity and information quantity, these descriptive means remain unconditional and can be misleading if the experimental groups differ on relevant participant characteristics. In this sample, financial literacy (and, to a lesser extent, Neuroticism) varies across conditions, and these factors may independently shape both decision quality and mental effort. Descriptive plots also do not quantify sampling uncertainty or account for the repeated-measures structure created by observing each participant across multiple complexity levels. For these reasons, I complement the descriptive results with regression models that estimate the complexity, information quantity, and interaction effects conditional on observed covariates (and appropriate within-participant dependence), providing a cleaner test of whether the patterns in the figures persist once plausible confounds are held constant.

4.3 Regression model

The effects of task complexity and information quantity on decision quality and self-rated mental effort are examined using the following model:

$$Y_{pi} = \alpha_1 + \beta_1\, \mathit{Complex}_{pi} + \beta_2\, \mathit{Info\_Quant}_p + \beta_3\, (\mathit{Complex}_{pi} \times \mathit{Info\_Quant}_p) + \gamma X_p + \varepsilon_{pi}. \quad (4.1)$$

where Y_{pi} denotes decision quality (the percentage correct in intrinsic value calculations and trading decisions) or self-rated mental effort for participant p at task complexity level i. Task complexity is coded as a centred numeric trend, *Complex* $\in \{-2,-1,0,1,2\}$ for levels 1-5 (0 corresponds to level 3), and information quantity is coded as *Info_Quant* $\in \{-1,0,1\}$ for levels 1-3 (0 corresponds to level 2). X_p is a vector of between-subject controls (gender, financial education, experience, financial literacy, risk tolerance, and the Big Five traits)[2], and standard errors are clustered by participant to account for repeated observations across complexity levels.

Under this coding, β_1 captures the expected change in Y for a one-step increase in task complexity when *Info_Quant* $= 0$ (information quantity level 2), β_2 captures the expected change in Y for a one-step increase in information quantity when *Complex* $= 0$ (task complexity level 3), and β_3 is the coefficient on the interaction term between task complexity and information quantity. In the model, the marginal effect of complexity equals $\beta_1 + \beta_3\, \mathit{Info\_Quant}$, so β_3 indicates how much the complexity slope shifts when information quantity increases by one level, holding the control variables fixed. A negative β_3 implies that the decline in performance associated with higher complexity becomes steeper under higher information load, whereas a positive β_3 would imply that the complexity effect attenuates as information increases.

4.4 Regression results

Table 4.3 presents linear regressions of participants' intrinsic value (IV) calculation accuracy as a function of task complexity and the quantity of information. The predictors are entered as centred numeric trends and all models include session fixed effects and individual-clustered standard errors. Column (1)[3] shows that each one-level increase in task complexity significantly, on average, reduces the IV calculation accuracy by 6.89 percentage points, while the results from column (2) present an average 12.10 percentage points lower accuracy associated with each one-level increase in information quantity. Both slope coefficients are statistically significant at the 1% level. These single-factor results already indicate a clear performance penalty from "more to process," whether that is harder tasks or more in-

[2] Since all participants are in the same age group, age is not included in the control variables set.

[3] Column (1) includes only the Task Complexity trend. Column (2) includes the Information Quantity trend only. Column (3) includes both trends and their interaction (Complexity $\times$ Information Quantity). Column (4) adds demographic/skill covariates (risk aversion, gender, financial education, investment experience, and financial literacy). Column (5) further includes the Big Five personality traits.

formation. In column (3), the coefficient of the interaction term is also statistically significant at the 1% level. The negative interaction implies that the penalty from one dimension intensifies as the other increases, indicating compounding load rather than simple additivity.

To interpret the interaction, it is helpful to translate the coefficients into marginal effects, that is, the expected change in accuracy from a one-level increase in one predictor while holding the other predictor fixed at a given level. Based on the results in Table 4.3, the one-step marginal effect of task complexity at a given information condition is

$$\beta_1 + \beta_3 \times \text{Info\_Quant},$$

where β_1 is the coefficient on task complexity and β_3 is the coefficient on the interaction term *Complex* $\times$ *Info_Quant*. Using the Column (3) estimates $\beta_1 = -0.0668$ and $\beta_3 = -0.0424$, the implied complexity slope under Condition 1 (low information load, Info_Quant $= -1$) is

$$-0.0668 + (-0.0424 \times -1) = -0.0244.$$

This corresponds to a 2.44 percentage-point reduction in IV calculation accuracy for each one-level increase in task complexity under low information load. Using the same method, the decreases in the medium information load (Condition 2) and the high information load (Condition 3) are 6.68 percentage points and 10.92 percentage points, respectively. Across the full task-complexity range, accuracy falls by 9.77 percentage points, 26.73 percentage points, and 43.69 percentage points in Conditions 1, 2, and 3, respectively.[4]

Given a mean IV calculation accuracy of about 60%[5], these coefficient magnitudes are economically meaningful. A 6.89 percentage-point decline per one-step increase in complexity corresponds to roughly an 11.48% reduction relative to the 60% baseline, while a 12.10 percentage-point decline per one-step increase in information quantity corresponds to about a 20.17% reduction. Under high information load, the implied complexity slope of 10.92 percentage points is around an 18.20% baseline-relative decline per step. Across the full complexity range under high information, the model-implied 43.69 percentage-point drop would move accuracy from 60% to roughly 16.31%, which is about a 72.82% reduction relative to the baseline level.

Likewise, the effect of information quantity is contingent on task complexity. At the lowest level of complexity, each one-step increase in information load reduces calculation accuracy by 3.66 percentage points. At moderate complexity (level 3) and at the highest complexity (level 5), the corresponding drops are 12.14 percentage points and 20.61 percentage points, respectively. Accordingly, moving from a low to a high information load results in a 7.31 percentage-point decrease in accuracy at complexity level 1, a 24.27 percentage-point decrease at level 3, and a 41.23 percentage-point decrease at the highest level.

Once demographic and psychological controls are added, very few individual-difference variables

[4] In linear trend models with integer coding, the change from level a to level b at fixed I equals $(b - a) \times (\beta_C + \beta_{CI} I)$. Because Complexity is coded $-2 \ldots +2$, $b - a = 4$ for the full-range contrast. Hence, the full-range change at each I equals $4 \times (\beta_C + \beta_{CI} I)$ (e.g., Condition 1: $4 \times (-0.0244) = -0.0976 \Rightarrow -9.77\%$).

[5] The "mean IV calculation accuracy" used as the baseline is the grand mean across the Study 1 sample. Specifically, for each participant, I first computed IV accuracy at each of the five task-complexity levels. I then averaged these accuracy values across the five complexity levels for that participant, and finally averaged the participant-level means across the pooled sample from Conditions 1-3 (low, medium, and high information load). This yields an unconditional grand mean that reflects the typical accuracy rate across all complexity and information-quantity settings in the study, rather than the predicted value at any single design point.

show robust associations with intrinsic value accuracy. In column (4), greater investment experience was modestly positively associated with accuracy, consistent with recent behavioral-finance evidence suggesting that investors learn from repeated market participation and gradually refine their decision-making processes (Jiang et al., 2024). By contrast, coefficients for risk aversion, gender, financial education, and financial literacy were small and statistically insignificant. This pattern aligns with finance research showing that gender and risk attitudes primarily predict participation and trading intensity. For example, work by Barber and Odean (2001) documents that men trade more and earn lower net returns than women, rather than basic computational accuracy on a given task, and studies indicate that financial literacy strongly predicts long-run outcomes such as retirement planning and stockholding but not necessarily performance on narrow, highly structured lab tasks (Lusardi & Mitchell, 2014). When the Big Five traits are added in column (5), only Extraversion showed a small positive association with calculation accuracy (around 4 percentage points), which is broadly in line with emerging evidence that more extraverted investors are somewhat more likely to engage with financial information and hold risky assets (Jiang et al., 2024; Treerotchananon et al., 2024; Yamane et al., 2025). However, the associated t-statistic is modest, and meta-analytic work in psychology shows that Big Five traits typically explain only a small share of variance in objective performance outcomes (Barrick & Mount, 1991), so this Extraversion effect is best viewed as suggestive rather than definitive. Taken together, these results are consistent with the idea that, in this experiment, structural features of the decision environment, task complexity and information quantity, are much more important determinants of calculation accuracy than stable demographic or personality characteristics, and that any incremental benefits of experience or extraversion are relatively modest once those task demands are taken into account.

In columns (4) and (5), the intercept declines and becomes insignificant in column (5). By contrast, the slope estimates, which are the primary quantities of interest, remain stable and strongly significant. In addition, adjusted R^2 improves from 0.147 to 0.225 in column (3) and to 0.245 in column (5), indicating meaningful explanatory gains from the interaction and modest incremental gains from controls.

Table 4.4 reports linear regressions of trading decision accuracy (proportion correct) on task complexity and information quantity. Trading decision accuracy declines with both task complexity and information quantity, and these two forces reinforce each other rather than acting additively. In column (3), each one-level increase in complexity is associated with approximately 7.59 percentage points lower accuracy at the information quantity level 2, while each one-level increase in information quantity carries an even larger penalty and results in 18.12 percentage points lower accuracy at task complexity level 3. The negative interaction term indicates that the decline associated with one dimension becomes steeper as the other increases. All coefficients are statistically significant at the 5% level or better.

With the centred trend coding used here, the marginal effect of complexity at a given information quantity level equals $\beta_1 + \beta_3\,\textit{Info\_Quant}$. This implies that complexity reduces accuracy by 5.38 percentage points per step under low information ($\textit{Info\_Quant} = -1$), by 7.59 percentage points per step at the medium information level ($\textit{Info\_Quant} = 0$), and by 9.80 percentage points per step under high information ($\textit{Info\_Quant} = 1$). Put differently, the same increase in complexity is materially more damaging when the information environment is dense, because the interaction shifts the complexity slope downward by about 2.21 percentage points each time information load rises by one level. The analogous calculation for information quantity is $\beta_2 + \beta_3\,\textit{Complex}$. At low complexity ($\textit{Complex} = -2$, level 1), a one-level increase in information quantity reduces accuracy by 13.70 percentage points; at moderate complexity (*Complex* $= 0$, level 3) the reduction is 18.12 percentage points; and at high complexity (*Complex* $= +2$, level 5) it reaches 22.54 percentage points. For example, moving from the lowest to the highest complexity level spans four one-step increases (-2 to $+2$). Under a high information quantity environment, this implies an expected decline of roughly $4 \times 9.80 \approx 39.2$ percentage points, compared with $4 \times 5.38 \approx 21.5$ percentage points under low information quantity environment, highlighting the compounding effect. These marginal effects show why the interaction is substantively meaningful. It does not simply add a constant penalty. Instead, it indicates that the performance cost of additional complexity grows as information increases, and the cost of additional information grows as complexity increases. The pattern remains robust when demographic/skill controls and Big Five traits (columns (4)-(5)) are added, despite their small and insignificant nature.

These gradients imply economically meaningful deterioration across the design space. With a mean trading accuracy of 54% in Conditions 1-3, the baseline complexity slope of 7.59 percentage points corresponds to roughly a 14.06% decline relative to the average accuracy level per one-step increase in complexity, while the information slope of 18.12 percentage points corresponds to about a 33.56% baseline-relative decline per one-step increase in information quantity. At the high-information-quantity end, the per-step complexity penalty of 9.80 percentage points is around 18.15% of the 54% baseline, and at the high-complexity end, the per-step information-quantity penalty of 22.54 percentage points is around 41.74% of baseline accuracy.

Given the model explains a meaningful share of variance for behavioral accuracy data (Adjusted $R^2 = 0.270$) and the key estimates are statistically significant ($p < 0.05$, with $p < 0.01$ for the main slopes), the evidence suggests that increases in the amount to process (information quantity) and the difficulty of processing (task complexity) each reduce trading decision quality, and that joint increases exacerbate this reduction in a way that is consistent with capacity-limit or cognitive-load mechanisms.

Table 4.5 reports linear regressions of self-rated mental effort on task complexity and information quantity. Participants rate their perceived workload on a 9-point Likert scale, ranging from 1 to 9. The mental effort sample size is slightly smaller due to some missing effort ratings. Column (3) indicates that self-rated mental effort increases with both task complexity and information quantity, with the coefficients being positive and statistically significant at the 5% level. At the design centre, each one-level increase in task complexity is associated with an increase of 0.17 points in perceived effort ($p < 0.01$), and each one-level increase in information quantity is associated with an increase of 0.62 points ($p < 0.01$). The interaction term is positive but not statistically significant, implying predominantly additive contributions.

The results in columns (4) and (5) show that including control variables and then the Big Five leaves the core pattern essentially unchanged. Adjusted R^2 rises from 0.078 (task complexity-only) and 0.117 (information quantity-only) to 0.128 with both trends and their interaction, and to 0.153-0.173 once controls and personality are added. For a repeated-measures self-report outcome, the increase in Adjusted R^2 across specifications is plausible. Most of the explanatory power is already captured by the two centred trends, while the control variables contribute only modest and fairly consistent additional improvement.

4.5 Results discussion

In general, the regressions indicate that both processing difficulty and the amount to process are costly. The more complex the task is and the more information people must process, the worse their performance gets. Participants' performance declines with each step up in task complexity or information quantity, and the drop is noticeably sharper when both are high (a significant negative interaction for intrinsic value calculation and trading decisions). At the same time, participants feel the strain, with their self-rated effort rising as either factor increases. That rise looks mostly additive rather than compounding, since the interaction for effort is small and not statistically significant.

In addition, including demographics/skills variables and subsequently the Big Five leaves the substantive conclusions unchanged. Estimated slopes for task complexity and information load in the accuracy models remain stable and precise. Similarly, the main effects of self-rated mental effort persist, the interaction remains insignificant, and model fit improves marginally. Associations for controls (e.g., small positive effects for investment experience on accuracy; minor shifts for gender/education/neuroticism on effort) are secondary and warrant cautious interpretation.

This pattern fits the Cognitive Load Theory (CLT) proposed by Sweller (1988). According to CLT, information acquired during decision-making is stored and processed in working memory, and cognitive overload occurs when an excess burden is placed on it due to individuals' processing capacity limitations. Working memory in human cognitive architecture is severely constrained in both capacity and duration, affecting how individuals acquire and process information (Baddeley, 1992; Miller, 1956). As the quantity of information increases, participants have more figures to keep track of, more intermediate steps to compute, and more opportunities to slip. Since all the information is relevant, it has to be encoded, organised, and integrated into investors' working memory before they can reach a final intrinsic value and trading decision. As explained in the Methodology section, this study does not assume that "more information makes the same decision better." Instead, participants are asked to make a closely matched decision that simply requires more of the same information, so any accuracy differences are not driven by better information but by the amount to be processed.

As the results show, the increase in information quantity is associated with significantly lower decision accuracy and higher perceived workload, consistent with hypotheses 1a and 1b about the limited capacity of humans' working memory. When the higher information quantity level adds two companies, the incremental load rises from 8 cues and 3 calculation steps at the lowest task complexity to 14 cues and 7 steps at the highest. Correspondingly, average accuracy declines by 12.10 percentage points for intrinsic value (IV) calculation and 18.12 percentage points for trading decisions. These magnitudes are economically meaningful. Relative to the average performance levels in Conditions 1-3, a 12.10 percentage-point decline in IV accuracy represents roughly a 20% reduction compared with a 60% baseline, while an 18.12 percentage-point decline in trading accuracy corresponds to about a 34% reduction relative to a 54% baseline. In other words, the information increase is not just statistically detectable; it translates into a sizeable deterioration in decision quality at the level of a typical participant.

The larger drop in trading is plausible. Under time pressure, participants may compute a fair value but lack time to translate it into the correct buy/hold/sell action, making the discrete trading decision more error-prone than the underlying calculation. Given the time-bounded setting, with each additional company in the question, participants use up more cognitive resources and make fewer correct calculations and lower trading performance, while reporting higher perceived mental effort. That combination is exactly what CLT would expect if working memory capacity is being pushed closer to its limit.

In this design, complexity is best viewed as the intrinsic source of cognitive load in CLT (more interacting steps/elements raise inherent processing demands), consistent with the updated CLT framework that distinguishes only intrinsic and extraneous load. CLT suggests that as stimulus complexity increases, working memory faces heavier demands, consuming additional resources for processing and mental manipulation. The results confirm this theory by showing that as the number of cues and element interactivity increases, the accuracy of both IV calculations and trading decisions suffers. As element interactivity rises, intrinsic load expands and quickly saturates limited working memory, leaving less capacity for schema-based processing and error checking.

The magnitudes are also economically meaningful. Within the three-minute regime, an increase of two information cues and/or one calculation step is associated with average declines of about 6.7 percentage points in IV calculation accuracy and 7.6 percentage points in trading decision accuracy. Relative to the average performance levels in Conditions 1-3, these correspond to roughly an 11% reduction against a 60% IV-accuracy baseline and about a 14% reduction against a 54% trading-accuracy baseline. Put differently, moving up only one notch of complexity shifts accuracy by a non-trivial fraction of typical performance, which is likely to matter in settings where small forecasting or trading errors compound over repeated decisions.

These results are consistent with hypotheses 2a and 2b. As complexity rises, individuals are more likely to move away from compensatory, full-information processing toward selective, heuristic strategies. Under time pressure, this shift can raise error risk in numeric finance tasks because fewer resources remain available for screening, integration, and verification. Additional components and stronger coupling therefore do more than add time; they absorb the scarce attentional and working-memory resources needed to integrate the right cues at the right moment. This mechanism also helps explain why subjective effort increases reliably with complexity even when participants attempt to maintain accuracy.

Beyond the main effects, the regression results show a significant interaction between task complexity and information quantity. At low complexity, increasing information quantity is associated with only a modest decline in intrinsic value accuracy and a moderate rise in self-rated mental effort. However, as complexity increases, the same increase in information quantity is associated with a much steeper drop in accuracy. In other words, the negative marginal effect of information quantity is amplified at higher levels of task complexity, and the detrimental impact of complexity is most pronounced when participants must process large information sets. This pattern suggests that the two manipulations do not simply add to intrinsic cognitive load but compound it, pushing participants into an overload region where additional effort cannot fully offset processing demands (Paas & Merriënboer, 1993; Iselin, 1988; Sweller, 1988). This is in line with CLT, which suggests that combining high element interactivity (complex tasks) with a large set of relevant cues produces a super-additive increase in cognitive load. Accordingly, participants report markedly higher mental effort but still make more errors, suggesting that working-memory limits have been exceeded. In addition, these findings extend the "information dimensions" approach (Iselin, 1988; Hwang & Lin, 1999) into the stock valuation context. When both the diversity of the task (five levels of complexity) and the quantity of information are high, decision quality declines more steeply than would be expected from either factor alone, consistent with a compounding effect of the diversity and repetition dimensions of information load.

Regarding self-rated mental effort, across all conditions, average ratings fall in the mid-to-high range of the scale, indicating that participants generally experienced the stock-valuation tasks as cognitively demanding rather than effortless. At the lowest level of task complexity and information quantity, mean effort is slightly above the neutral midpoint (around 5 on the 1-9 scale), suggesting a moderate cognitive load even in the simplest condition. Mental-effort ratings then rise systematically with increases in both task complexity and information quantity, with the highest values observed when participants face the most complex problems combined with the largest information sets.

In the regression models, both task complexity and information quantity show positive and statistically significant coefficients for self-rated effort, and the Complex $\times$ Info_Quant interaction term is also positive but insignificant. This pattern implies that more complex valuation problems are experienced as more effortful, and that processing additional information further elevates perceived effort. At the same time, the insignificance of the interaction term provides limited support for the view that the two manipulations increase effort in a more-than-additive way within the range tested.

The mental-effort results confirm that the manipulations of task complexity and information quantity successfully increased intrinsic cognitive load. Effort ratings rise steadily with both factors and peak when both are high, indicating that participants experience those conditions as cognitively overwhelming. Coupled with the simultaneous decline in decision accuracy, this pattern is consistent with classic information-overload findings in accounting-style decision tasks (Iselin, 1988) and with CLT's prediction that, once intrinsic load exceeds working-memory capacity, additional effort no longer translates into better performance. From a CLT perspective, this pattern signals inefficient processing. Participants report higher mental effort, yet accuracy still declines, suggesting that the intrinsic demands of the task may exceed working-memory capacity within the range tested. Paas and van Merriënboer (1993)'s efficiency framework explicitly treats this configuration, high mental effort combined with relatively poor performance, as evidence of cognitive overload rather than productive engagement.

In this study, the pattern of monotonic declines in calculation and trading decision accuracy as task complexity and information quantity increase sits naturally within the broader literature on limited attention and processing capacity. Rational-inattention models formalise the idea that decision makers optimise under a finite "information bandwidth," choosing which signals to encode and how precisely, rather than processing all available information in full detail (Peng, 2005; Peng & Xiong, 2006; Sims, 2003). In these models, performance deteriorates once task demands exceed processing capacity, not because agents suddenly become careless, but because additional precision or additional signals are no longer worth the marginal attentional cost. This economic perspective closely parallels capacity models of attention in psychology, which treat attention as a limited mental resource that must be allocated across concurrent demands (Kahneman, 1973; Cowan, 2010). Evidence on working-memory limits suggests that adults can actively maintain only around three to four "chunks" of information at a time. When more elements must be tracked and integrated, accuracy and speed systematically decline (Cowan, 2001; Pashler, 1994).

In this design, higher complexity and larger information sets both increase the number of interacting elements that must be held and combined in working memory, so the observed smooth deterioration in performance as these factors rise is exactly what a capacity-limited system would predict. The results also echo a broad empirical finance tradition documenting that investors attend selectively to a small subset of salient signals, leaving other information underprocessed. For example, individual investors are net buyers of attention-grabbing stocks and underreact to more routine news (Barber & Odean, 2008, 2013; DellaVigna & Pollet, 2009), and direct measures of attention show that limited attention distorts short-run prices and trading behaviour (Choi & Choi, 2019). Seen through this lens, the consistent declines in the accuracy of calculations and trading decisions in Study 1 as complexity and information quantity increase are not anomalies. They can be read as a micro-level manifestation of the same capacity constraints that rational-inattention theory and investor-attention evidence describe at the market level.

4.6 Robustness check

To assess the sensitivity of these findings, I re-estimate the models on a restricted sample that excludes any participant who recorded 0% accuracy at any task-complexity level (yielding $N = 96$). Results for intrinsic value (IV) calculation accuracy, trading decision accuracy, and self-rated mental effort are reported in Tables 4.6-4.8. The substantive pattern is unchanged. The core slopes for information quantity and task complexity remain stable and are significant at the 1% level. As tasks become more complex and as information quantity increases, objective performance declines (for both IV calculations and trading decisions), while subjective mental effort rises. When high complexity and high information load coincide, performance losses compound, and the interaction is clear in the accuracy models, whereas effort increases in a largely additive fashion (the interaction is small and not statistically significant). Adding controls (demographics/skills, then Big Five) leaves the key effects essentially unchanged. Taken together, the combination of declining accuracy, rising effort, and a muted interaction in effort is consistent with a limited-capacity account. Participants report higher workload as demands increase, yet error rates appear to rise faster than subjective effort ratings adjust to reflect the compounding difficulty.

Second, I run robustness regressions that drop cluster-adjusted standard errors and remove session fixed effects. As reported in Tables 4.9-4.11, the estimates are very similar to the originals, with only minor, non-substantive differences.

I also verify the core patterns using a mixed repeated-measures ANOVA, with task complexity as the within-subject factor and information quantity as the between-subject factor. For IV accuracy, Mauchly's test in Table 4.12a indicates a violation of sphericity for complexity ($W = 0.708$, $\chi^2 = 55.81$, $p < 0.001$), so I apply the Huynh–Feldt correction ($\varepsilon = 0.869$). The main effect of complexity in Table 4.12b is significant under the Huynh–Feldt correction ($p < 0.001$), and the main effect of information quantity in Table 4.12c is also significant ($F = 16.94$, $p < 0.001$). Crucially, the Complex $\times$ Info_Quant interaction in Table 4.12b is significant under the Huynh–Feldt correction ($p < 0.001$), and a multivariate test corroborates this (Pillai's Trace $= 0.151$, $F(8, 322) = 3.30$, $p = 0.001$). The corresponding ANOVA results for trading decision accuracy[6] in Table 4.13 and self-rated mental effort

[6]For trading-decision accuracy, the mixed repeated-measures ANOVA shows a significant within-subject main effect of complexity ($F = 34.92$, $p < 0.001$) and a significant between-subject main effect of condition ($F = 40.20$, $p < 0.001$). The omnibus complexity $\times$ condition interaction is not statistically significant in the within-subjects table ($F = 1.28$, $p = 0.249$; Greenhouse–Geisser $p = 0.251$; Huynh–Feldt $p = 0.249$), and the multivariate test is also non-significant (Pillai's Trace $= 0.052$, $F(8, 322) = 1.07$, $p = 0.384$). However, the planned linear contrast for complexity $\times$ condition is significant ($F = 4.07$, $p = 0.019$), which is the contrast most directly comparable to the regression specification that models complexity

in Table 4.14 show a similar pattern.

Furthermore, given the female-majority composition of the student sample, an additional robustness analysis examines whether the principal findings are sensitive to observable gender differences. The analysis is restricted to participants identifying as male or female. Female participants are reweighted using entropy balancing so that their mean levels of financial education, investment experience, and financial literacy match those of male participants. Entropy balancing is preferred to one-to-one propensity score matching because the number of female participants substantially exceeds the number of male participants, and one-to-one matching would result in a considerable loss of observations. The participant-level entropy weights are applied consistently across the five repeated observations for each participant. The main Study 1 regressions are then re-estimated using these weights while retaining the original session fixed effects, participant-level controls, and standard errors clustered at the participant level. The principal results in Table 4.15 remain highly consistent with the original estimates, indicating that the effects of task complexity, information quantity, and their interaction are not driven by the gender composition of the sample.

These additional checks reinforce the robustness of the findings. Task complexity and information quantity exert significantly negative pressure on computation and decision quality, and a positive effect on perceived effort, with the interaction apparent for accuracy but not for effort.

and information quantity as centred numeric trends.

Table 4.1: Descriptive Statistics

Panel A. Descriptive statistics by condition

	Condition 1 ($N = 52$)					Condition 2 ($N = 54$)					Condition 3 ($N = 60$)				
Variable	Mean	Median	Stdev	Min	Max	Mean	Median	Stdev	Min	Max	Mean	Median	Stdev	Min	Max
Risk Aversion	2.27	2.00	1.12	1.00	4.00	2.37	2.00	1.00	1.00	4.00	2.33	2.00	1.07	1.00	4.00
Age	1.00	1.00	0.00	1.00	1.00	1.00	1.00	0.00	1.00	1.00	1.02	1.00	0.13	1.00	2.00
Gender	1.79	2.00	0.54	1.00	4.00	1.72	2.00	0.49	1.00	3.00	1.75	2.00	0.47	1.00	3.00
Financial Education	2.75	3.00	0.97	1.00	6.00	2.85	3.00	0.86	2.00	6.00	2.65	3.00	0.82	1.00	6.00
Investment experience	1.35	1.00	0.56	1.00	3.00	1.28	1.00	0.45	1.00	2.00	1.47	1.00	0.68	1.00	4.00
Financial Literacy	4.42	5.00	0.78	2.00	5.00	3.98	4.00	0.98	1.00	5.00	3.67	4.00	1.31	0.00	5.00
Extraversion	3.85	3.75	1.01	1.00	6.00	3.69	3.75	0.68	1.75	5.00	3.50	3.50	0.95	1.25	5.50
Agreeableness	4.51	4.75	0.89	1.00	6.00	4.69	5.00	0.78	2.50	6.00	4.46	4.50	0.78	1.75	5.75
Conscientiousness	4.14	4.25	0.87	2.25	6.00	4.32	4.50	0.76	2.50	5.50	4.18	4.25	0.68	2.25	5.75
Neuroticism	3.86	4.00	1.08	1.50	6.00	4.29	4.38	0.97	1.25	5.75	4.35	4.50	0.94	2.00	6.00
Openness	4.31	4.50	0.84	1.00	6.00	4.42	4.50	0.76	2.75	5.75	4.32	4.25	0.71	1.50	5.75

Panel B. Balance tests (pairwise comparisons)

	Condition 1 vs Condition 2				Condition 1 vs Condition 3				Condition 2 vs Condition 3			
	Test of difference in mean		Test of difference in median		Test of difference in mean		Test of difference in median		Test of difference in mean		Test of difference in median	
Variable	Mean	p-value	Median	p-value	Mean	p-value	Median	p-value	Mean	p-value	Median	p-value
Risk Aversion	-0.10	0.63	0.00	0.59	-0.06	0.76	0.00	0.73	0.04	0.85	0.00	0.80
Age			0.00	1.00	-0.02	0.32	0.00	0.35	-0.02	0.32	0.00	0.34
Gender	0.07	0.51	0.00	0.60	0.04	0.69	0.00	0.83	-0.03	0.76	0.00	0.75
Financial Education	-0.10	0.57	0.00	0.34	0.10	0.56	0.00	0.78	0.20	0.20	0.00	0.22
Investment experience	0.07	0.49	0.00	0.65	-0.12	0.30	0.00	0.37	-0.19	0.08	0.00	0.17
Financial Literacy	0.44	0.01**	1.00	0.02**	0.76	< 0.001***	1.00	< 0.001***	0.32	0.15	0.00	0.34
Extraversion	0.16	0.34	0.00	0.34	0.34	0.07	0.25	0.07	0.18	0.24	0.25	0.25
Agreeableness	-0.18	0.27	-0.25	0.24	0.05	0.75	0.25	0.56	0.23	0.12	0.50	0.11
Conscientiousness	-0.18	0.25	-0.25	0.18	-0.04	0.81	0.00	0.82	0.15	0.28	0.25	0.15
Neuroticism	-0.43	0.04**	-0.38	0.03**	-0.49	0.01**	-0.50	0.02**	-0.06	0.74	-0.13	0.85
Openness	-0.11	0.47	0.00	0.42	-0.01	0.93	0.25	0.83	0.10	0.47	0.25	0.43

Note: The table reports summary statistics for the full sample ($N = 166$) and, separately, for Condition 1 ($N = 52$), Condition 2 ($N = 54$), and Condition 3 ($N = 60$). For each variable, it lists the mean, median, standard deviation (Stdev), and observed range, followed by pairwise balance tests (C1 vs C2, C1 vs C3, C2 vs C3) using both mean and median tests.

Table 4.2: Correlations

	1	2	3	4	5	6	7	8	9	10	11
1 Risk Aversion	1										
2 Age	0.124	1									
3 Gender	-0.319**	-0.118	1								
4 Financial Education	-0.107	-0.155*	0.133	1							
5 Investment experience	0.171*	0.086	-0.337**	-0.187*	1						
6 Financial Literacy	0.118	0.000	-0.175*	0.090	0.083	1					
7 Extraversion	0.147	-0.102	-0.007	-0.126	0.107	0.148	1				
8 Agreeableness	-0.052	-0.005	-0.030	-0.154*	-0.033	0.086	0.291**	1			
9 Conscientiousness	-0.134	-0.022	0.011	-0.236**	0.007	-0.059	0.130	0.458**	1		
10 Neuroticism	-0.085	0.006	0.143	0.077	-0.080	-0.038	-0.093	0.126	-0.040	1	
11 Openness	0.128	-0.087	-0.162*	-0.151	0.089	0.118	0.424**	0.442**	0.397**	0.033	1

Note: This table presents the Pearson correlation matrix of the participant characteristics.

Table 4.3: Effect of Task Complexity and Information Quantity on Intrinsic Value calculation accuracy (Full sample of conditions 1, 2, and 3)

	(1)	(2)	(3)	(4)	(5)
Intercept	0.7310***	0.7569***	0.7569***	0.5877***	0.3146
	(14.80)	(17.94)	(17.92)	(3.48)	(1.31)
Complex	-0.0689***		-0.0668***	-0.0668***	-0.0668***
	(-8.71)		(-8.90)	(-8.88)	(-8.85)
Info_Quant		-0.1210***	-0.1210***	-0.1241***	-0.1214***
		(-4.76)	(-4.76)	(-4.74)	(-4.54)
Complex × Info_Quant			-0.0424***	-0.0424***	-0.0424***
			(-5.10)	(-5.08)	(-5.07)
Risk Aversion				0.0094	0.0068
				(0.49)	(0.34)
Gender				0.0528	0.0435
				(1.18)	(0.96)
Fin_edu				0.0158	0.0085
				(0.65)	(0.38)
Invest_Exp				0.0690**	0.0634*
				(1.98)	(1.86)
Fin_literacy				0.0012	-0.0078
				(0.06)	(-0.41)
Extraversion					0.0416*
					(1.73)
Agreeableness					0.0317
					(1.13)
Conscientiousness					-0.0007
					(-0.03)
Neuroticism					0.0107
					(0.55)
Openness					-0.0050
					(-0.15)
Adj. R^2	0.147	0.138	0.225	0.233	0.245
Observations	830	830	830	830	830
Standard errors adjusted for clustering	Individual	Individual	Individual	Individual	Individual
Fixed effect (session)	Yes	Yes	Yes	Yes	Yes

Note: The table reports OLS regressions at the task level. Predictors are entered as centred numeric trends. All models include session fixed effects, and inference is based on participant-clustered (cluster-robust) t-statistics reported in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. The dependent variable is participants' intrinsic value (IV) calculation accuracy (proportion correct). Column (1) includes only the Task Complexity trend. Column (2) includes the Information Quantity trend only. Column (3) includes both trends and their interaction (Complexity × Information Quantity). Column (4) adds demographic/skill covariates (risk aversion, gender, financial education, investment experience, and financial literacy). Column (5) further includes the Big Five personality traits.

Table 4.4: Effect of Task Complexity and Information Quantity on trading decision accuracy (Full sample of conditions 1, 2, and 3)

	(1)	(2)	(3)	(4)	(5)
Intercept	0.6262***	0.6650***	0.6650***	0.6243***	0.4366*
	(8.91)	(11.88)	(11.86)	(3.92)	(1.85)
Complex	-0.0770***		-0.0759***	-0.0759***	-0.0759***
	(-10.28)		(-10.23)	(-10.20)	(-10.17)
Info_Quant		-0.1812***	-0.1812***	-0.1795***	-0.1846***
		(-8.10)	(-8.09)	(-7.70)	(-7.80)
Complex × Info_Quant			-0.0221**	-0.0221**	-0.0221**
			(-2.45)	(-2.44)	(-2.43)
Risk Aversion				-0.0156	-0.0190
				(-0.94)	(-1.12)
Gender				0.0197	0.0163
				(0.52)	(0.43)
Fin_edu				0.0096	0.0078
				(0.37)	(0.32)
Invest_Exp				0.0238	0.0212
				(0.71)	(0.66)
Fin_literacy				0.0090	0.0030
				(0.50)	(0.16)
Extraversion					0.0249
					(1.13)
Agreeableness					-0.0142
					(-0.54)
Conscientiousness					0.0025
					(0.09)
Neuroticism					0.0208
					(1.11)
Openness					0.0233
					(0.71)
Adj. R^2	0.143	0.188	0.270	0.270	0.273
Observations	830	830	830	830	830
Standard errors adjusted for clustering	Individual	Individual	Individual	Individual	Individual
Fixed effect (session)	Yes	Yes	Yes	Yes	Yes

Note: The table reports OLS regressions at the task level. Predictors are entered as centred numeric trends. All models include session fixed effects, and inference is based on participant-clustered (cluster-robust) t-statistics reported in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Dependent variable is trading decision accuracy (proportion correct). Column specifications are as in Table 4.3.

Table 4.5: Effect of Task Complexity and Information Quantity on self-rated mental effort (Full sample of conditions 1, 2, and 3)

	(1)	(2)	(3)	(4)	(5)
Intercept	5.8000***	5.6665***	5.6666***	3.0421**	1.6086
	(11.79)	(11.89)	(11.88)	(2.55)	(0.95)
Complex	0.1689***		0.1667***	0.1646***	0.1645***
	(4.74)		(4.73)	(4.63)	(4.61)
Info_Quant		0.6230***	0.6224***	0.6236***	0.4920***
		(3.40)	(3.39)	(3.44)	(2.62)
Complex × Info_Quant			0.0418	0.0415	0.0409
			(1.00)	(0.99)	(0.97)
Risk Aversion				-0.0304	0.0248
				(-0.25)	(0.21)
Gender				0.5873*	0.6092*
				(1.73)	(1.87)
Fin_edu				-0.2478*	-0.2318
				(-1.66)	(-1.53)
Invest_Exp				0.3298	0.4166
				(1.26)	(1.61)
Fin_literacy				0.0352	0.0078
				(0.37)	(0.08)
Extraversion					-0.2236
					(-1.47)
Agreeableness					0.1060
					(0.47)
Conscientiousness					0.0534
					(0.23)
Neuroticism					0.2603*
					(1.91)
Openness					0.0647
					(0.28)
Adj. R^2	0.078	0.117	0.128	0.153	0.173
Observations	805	805	805	805	805
Standard errors adjusted for clustering	Individual	Individual	Individual	Individual	Individual
Fixed effect (session)	Yes	Yes	Yes	Yes	Yes

Note: The table reports OLS regressions at the task level. Predictors are entered as centred numeric trends. All models include session fixed effects, and inference is based on participant-clustered (cluster-robust) t-statistics reported in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Dependent variable is self-rated mental effort (1-9 scale). Column specifications are as in Table 4.3.

Table 4.6: Effect of Task Complexity and Information Quantity on intrinsic value calculation accuracy (Restricted sample of conditions 1, 2, and 3)

	(1)	(2)	(3)	(4)	(5)
Intercept	0.7736***	0.8093***	0.8093***	0.6835***	0.5554***
	(18.09)	(33.32)	(33.25)	(6.92)	(3.31)
Complex	-0.0691***		-0.0697***	-0.0697***	-0.0697***
	(-8.62)		(-11.15)	(-11.09)	(-11.03)
Info_Quant		-0.1429***	-0.1429***	-0.1403***	-0.1365***
		(-8.16)	(-8.14)	(-7.77)	(-6.68)
Complex × Info_Quant			-0.0564***	-0.0564***	-0.0564***
			(-8.62)	(-8.58)	(-8.53)
Risk Aversion				0.0155	0.0154
				(1.13)	(1.02)
Gender				0.0080	-0.0161
				(0.28)	(-0.50)
Fin_edu				-0.0040	-0.0106
				(-0.25)	(-0.59)
Invest_Exp				0.0182	0.0126
				(0.79)	(0.52)
Fin_literacy				0.0115	0.0073
				(0.79)	(0.51)
Extraversion					0.0211
					(1.20)
Agreeableness					0.0476**
					(2.39)
Conscientiousness					0.0107
					(0.48)
Neuroticism					-0.0079
					(-0.65)
Openness					-0.0321
					(-1.18)
Adj. R^2	0.219	0.251	0.460	0.463	0.473
Observations	480	480	480	480	480
Standard errors adjusted for clustering	Individual	Individual	Individual	Individual	Individual
Fixed effect (session)	Yes	Yes	Yes	Yes	Yes

Note: The table reports OLS regressions at the task level. Predictors are entered as centred numeric trends. All models include session fixed effects, and inference is based on participant-clustered (cluster-robust) t-statistics reported in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Dependent variable is IV calculation accuracy (proportion correct). Restricted sample excludes participants who recorded 0% IV accuracy at any task-complexity level. Column specifications are as in Table 4.3.

Table 4.7: Effect of Task Complexity and Information Quantity on trading decision accuracy (Restricted sample of conditions 1, 2, and 3)

	(1)	(2)	(3)	(4)	(5)
Intercept	0.6806***	0.7295***	0.7295***	0.6855***	0.6795***
	(9.73)	(17.29)	(17.25)	(5.10)	(3.16)
Complex	-0.0834***		-0.0839***	-0.0839***	-0.0839***
	(-9.60)		(-10.94)	(-10.89)	(-10.83)
Info_Quant		-0.1956***	-0.1956***	-0.1949***	-0.1901***
		(-9.22)	(-9.20)	(-8.70)	(-8.02)
Complex × Info_Quant			-0.0460***	-0.0460***	-0.0460***
			(-5.26)	(-5.23)	(-5.20)
Risk Aversion				-0.0085	-0.0071
				(-0.50)	(-0.39)
Gender				-0.0048	-0.0180
				(-0.14)	(-0.45)
Fin_edu				-0.0260	-0.0298
				(-1.34)	(-1.40)
Invest_Exp				0.0110	0.0056
				(0.34)	(0.17)
Fin_literacy				-0.0030	-0.0045
				(-0.15)	(-0.22)
Extraversion					0.0195
					(1.00)
Agreeableness					-0.0039
					(-0.13)
Conscientiousness					0.0194
					(0.65)
Neuroticism					0.0010
					(0.06)
Openness					-0.0273
					(-0.80)
Adj. R^2	0.179	0.248	0.392	0.391	0.387
Observations	480	480	480	480	480
Standard errors adjusted for clustering	Individual	Individual	Individual	Individual	Individual
Fixed effect (session)	Yes	Yes	Yes	Yes	Yes

Note: The table reports OLS regressions at the task level. Predictors are entered as centred numeric trends. All models include session fixed effects, and inference is based on participant-clustered (cluster-robust) t-statistics reported in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Dependent variable is trading decision accuracy (proportion correct). Restricted sample defined as in Table 4.6. Column specifications are as in Table 4.3.

Table 4.8: Effect of Task Complexity and Information Quantity on self-rated mental effort (Restricted sample of conditions 1, 2, and 3)

	(1)	(2)	(3)	(4)	(5)
Intercept	5.4833***	5.3733***	5.3738***	4.4263***	1.4047
	(10.51)	(10.63)	(10.61)	(3.70)	(0.65)
Complex	0.2432***		0.2429***	0.2437***	0.2434***
	(5.33)		(5.29)	(5.28)	(5.25)
Info_Quant		0.4403*	0.4380*	0.4939**	0.3724
		(1.78)	(1.77)	(2.06)	(1.56)
Complex × Info_Quant			0.0472	0.0477	0.0479
			(0.84)	(0.84)	(0.84)
Risk Aversion				-0.1817	-0.2375
				(-1.15)	(-1.47)
Gender				0.0090	0.1614
				(0.02)	(0.38)
Fin_edu				-0.3192*	-0.2561*
				(-1.89)	(-1.69)
Invest_Exp				-0.0824	-0.0548
				(-0.22)	(-0.14)
Fin_literacy				0.1592	0.1755
				(1.08)	(1.07)
Extraversion					-0.0678
					(-0.31)
Agreeableness					0.1771
					(0.51)
Conscientiousness					-0.1324
					(-0.46)
Neuroticism					0.2075
					(1.21)
Openness					0.4984
					(1.36)
Adj. R^2	0.128	0.126	0.152	0.173	0.198
Observations	472	472	472	472	472
Standard errors adjusted for clustering	Individual	Individual	Individual	Individual	Individual
Fixed effect (session)	Yes	Yes	Yes	Yes	Yes

Note: The table reports OLS regressions at the task level. Predictors are entered as centred numeric trends. All models include session fixed effects, and inference is based on participant-clustered (cluster-robust) t-statistics reported in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Dependent variable is self-rated mental effort (1-9 scale). Restricted sample defined as in Table 4.6. Column specifications are as in Table 4.3.

Table 4.9: Robustness check: Effects of task complexity and information quantity on IV calculation accuracy (no session fixed effects; non-clustered standard errors)

	(1)	(2)	(3)	(4)	(5)
Intercept	0.5976***	0.6041***	0.6041***	0.4554***	0.0899
	(48.38)	(49.29)	(51.51)	(5.14)	(0.64)
Complex	-0.0689***		-0.0668***	-0.0668***	-0.0668***
	(-7.86)		(-8.21)	(-8.31)	(-8.42)
Info_Quant		-0.1351***	-0.1351***	-0.1452***	-0.1476***
		(-9.27)	(-9.82)	(-10.20)	(-10.26)
Complex × Info_Quant			-0.0424***	-0.0424***	-0.0424***
			(-4.59)	(-4.61)	(-4.71)
Risk Aversion				0.0118	0.0102
				(1.05)	(0.90)
Gender				0.0642**	0.0521**
				(2.57)	(2.10)
Fin_edu				0.0170	0.0091
				(1.21)	(0.64)
Invest_Exp				0.0795***	0.0786***
				(4.01)	(4.06)
Fin_literacy				-0.0132	-0.0202*
				(-1.19)	(-1.81)
Extraversion					0.0374**
					(2.57)
Agreeableness					0.0232
					(1.36)
Conscientiousness					0.0029
					(0.16)
Neuroticism					0.0297**
					(2.54)
Openness					0.0044
					(0.22)
Adj. R^2	0.069	0.089	0.175	0.191	0.207
Observations	830	830	830	830	830
Standard errors adjusted for clustering	No	No	No	No	No
Fixed effect (session)	No	No	No	No	No

Note: The table reports OLS regressions at the task level. Predictors are entered as centred numeric trends. The specifications do not use clustered standard errors for individuals and do not include session fixed effects. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Dependent variable is participants' intrinsic value (IV) calculation accuracy (proportion correct).

Table 4.10: Robustness check: Effects of task complexity and information quantity on trading decision accuracy (no session fixed effects; non-clustered standard errors)

	(1)	(2)	(3)	(4)	(5)
Intercept	0.5324***	0.5417***	0.5417***	0.5212***	0.2545*
	(41.06)	(43.72)	(45.88)	(5.74)	(1.77)
Complex	-0.0770***		-0.0759***	-0.0759***	-0.0759***
	(-8.46)		(-9.18)	(-9.21)	(-9.30)
Info_Quant		-0.1920***	-0.1920***	-0.1947***	-0.2014***
		(-12.88)	(-13.43)	(-12.92)	(-13.15)
Complex × Info_Quant			-0.0221**	-0.0221**	-0.0221**
			(-2.22)	(-2.22)	(-2.26)
Risk Aversion				-0.0152	-0.0179
				(-1.32)	(-1.54)
Gender				0.0374	0.0281
				(1.47)	(1.11)
Fin_edu				0.0149	0.0121
				(1.01)	(0.83)
Invest_Exp				0.0314	0.0289
				(1.44)	(1.35)
Fin_literacy				-0.0029	-0.0071
				(-0.25)	(-0.62)
Extraversion					0.0217
					(1.46)
Agreeableness					-0.0173
					(-0.98)
Conscientiousness					0.0079
					(0.41)
Neuroticism					0.0349***
					(2.87)
Openness					0.0281
					(1.40)
Adj. R^2	0.077	0.163	0.244	0.246	0.255
Observations	830	830	830	830	830
Standard errors adjusted for clustering	No	No	No	No	No
Fixed effect (session)	No	No	No	No	No

Note: The table reports OLS regressions at the task level. Predictors are entered as centred numeric trends. The specifications do not use clustered standard errors for individuals and do not include session fixed effects. Significance levels: $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Dependent variable is participants' trading decision accuracy (proportion correct).

Table 4.11: Robustness check: Effects of task complexity and information quantity on self-rated mental effort (no session fixed effects; non-clustered standard errors)

	(1)	(2)	(3)	(4)	(5)
Intercept	6.0750***	6.0542***	6.0547***	4.1558***	3.3520***
	(83.08)	(84.14)	(84.64)	(7.58)	(3.54)
Complex	0.1701***		0.1687***	0.1667***	0.1667***
	(3.24)		(3.27)	(3.27)	(3.28)
Info_Quant		0.6050***	0.6052***	0.6453***	0.5749***
		(7.02)	(7.08)	(7.27)	(6.31)
Complex × Info_Quant			0.0417	0.0413	0.0408
			(0.68)	(0.69)	(0.69)
Risk Aversion				-0.0495	-0.0150
				(-0.75)	(-0.22)
Gender				0.5455***	0.5943***
				(2.90)	(3.18)
Fin_edu				-0.2010**	-0.1948**
				(-2.55)	(-2.24)
Invest_Exp				0.0868	0.1466
				(0.63)	(1.05)
Fin_literacy				0.0936	0.0926
				(1.61)	(1.55)
Extraversion					-0.2557***
					(-2.92)
Agreeableness					0.1073
					(0.91)
Conscientiousness					-0.0043
					(-0.04)
Neuroticism					0.1036
					(1.44)
Openness					0.1418
					(1.13)
Adj. R^2	0.012	0.055	0.067	0.089	0.097
Observations	805	805	805	805	805
Standard errors adjusted for clustering	No	No	No	No	No
Fixed effect (session)	No	No	No	No	No

Note: The table reports OLS regressions at the task level. Predictors are entered as centred numeric trends. The specifications do not use clustered standard errors for individuals and do not include session fixed effects. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Dependent variable is participants' self-rated mental effort.

Table 4.12a: Robustness check. Mixed repeated-measures ANOVA. Mauchly's test of sphericity for task complexity (IV calculation accuracy)

Mauchly's Test of Sphericity[a]
Measure: `IV accuracy`

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	*df*	Sig.	Epsilon[b]		
					Greenhouse–Geisser	Huynh–Feldt	Lower-bound
IV	0.708	55.812	9	$< .001$	0.839	0.869	0.250

Note: Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

[a] Design: Intercept + Condition. Within Subjects Design: IV.
[b] May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

Note: The sphericity diagnostic for the within-subject factor (task complexity), including Greenhouse–Geisser and Huynh–Feldt epsilon values used for correction.

Table 4.12b: Robustness check. Mixed repeated-measures ANOVA. Within-subject effects of task complexity and task complexity by information quantity (IV calculation accuracy)

Tests of Within-Subjects Effects
Measure: `IV accuracy`

Source		Type III Sum of Squares	*df*	Mean Square	*F*	Sig.
IV	Sphericity Assumed	79051.744	4.000	19762.936	35.809	$<.001$
	Greenhouse–Geisser	79051.744	3.356	23557.913	35.809	$<.001$
	Huynh–Feldt	79051.744	3.477	22737.590	35.809	$<.001$
	Lower-bound	79051.744	1.000	79051.744	35.809	$<.001$
IV $\times$ Condition	Sphericity Assumed	23064.964	8.000	2883.121	5.224	$<.001$
	Greenhouse–Geisser	23064.964	6.711	3436.752	5.224	$<.001$
	Huynh–Feldt	23064.964	6.953	3317.079	5.224	$<.001$
	Lower-bound	23064.964	2.000	11532.482	5.224	0.006
Error(IV)	Sphericity Assumed	359838.818	652.000	551.900		
	Greenhouse–Geisser	359838.818	546.968	657.879		
	Huynh–Feldt	359838.818	566.702	634.970		
	Lower-bound	359838.818	163.000	2207.600		

Note: The F-tests for the within-subject main effect (task complexity) and the within-subject interaction (task complexity $\times$ information quantity/condition), reported under sphericity assumed and corrected degrees of freedom.

Table 4.12c: Robustness check. Mixed repeated-measures ANOVA. Between-subject effect of information quantity (IV calculation accuracy)

Tests of Between-Subjects Effects
Measure: `IV accuracy`
Transformed Variable: Average

Source	Type III Sum of Squares	*df*	Mean Square	*F*	Sig.
Intercept	3012371.058	1	3012371.058	898.513	$< .001$
Condition	113613.987	2	56806.993	16.944	$< .001$
Error	546476.709	163	3352.618		

Note: The between-subject F-test for the main effect of information quantity (condition), based on the participant-level average across complexity levels.

Table 4.13a: Robustness check. Mixed repeated-measures ANOVA. Mauchly's test of sphericity for task complexity (Trading decision accuracy)

Mauchly's Test of Sphericity[a]
Measure: `Trading decision accuracy`

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	*df*	Sig.	Epsilon[b]		
					Greenhouse–Geisser	Huynh–Feldt	Lower-bound
Trading_Decisions	0.937	10.434	9	0.317	0.969	1.000	0.250

Note: Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

[a] Design: Intercept + Condition. Within Subjects Design: Trading_Decisions.
[b] May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

Note: The sphericity diagnostic for the within-subject factor (task complexity), including Greenhouse–Geisser and Huynh–Feldt epsilon values used for correction.

Table 4.13b: Robustness check. Mixed repeated-measures ANOVA. Within-subject effects of task complexity and task complexity by information quantity (Trading decision accuracy)

Tests of Within-Subjects Effects
Measure: `Trading decision accuracy`

Source		Type III Sum of Squares	*df*	Mean Square	*F*	Sig.
Trading_Decisions	Sphericity Assumed	102563.956	4.000	25640.989	34.915	$<.001$
	Greenhouse–Geisser	102563.956	3.875	26470.404	34.915	$<.001$
	Huynh–Feldt	102563.956	4.000	25640.989	34.915	$<.001$
	Lower-bound	102563.956	1.000	102563.956	34.915	$<.001$
Trading_Decisions × Condition	Sphericity Assumed	7537.926	8.000	942.241	1.283	0.249
	Greenhouse–Geisser	7537.926	7.749	972.720	1.283	0.251
	Huynh–Feldt	7537.926	8.000	942.241	1.283	0.249
	Lower-bound	7537.926	2.000	3768.963	1.283	0.280
Error(Trading_Decisions)	Sphericity Assumed	478814.316	652.000	734.378		
	Greenhouse–Geisser	478814.316	631.570	758.133		
	Huynh–Feldt	478814.316	652.000	734.378		
	Lower-bound	478814.316	163.000	2937.511		

Note: The F-tests for the within-subject main effect (task complexity) and the within-subject interaction (task complexity × information quantity/condition), reported under sphericity assumed and corrected degrees of freedom.

Table 4.13c: Robustness check. Mixed repeated-measures ANOVA. Between-subject effect of information quantity/condition (Trading decision accuracy)

Tests of Between-Subjects Effects
Measure: `Trading decision accuracy`
Transformed Variable: Average

Source	Type III Sum of Squares	*df*	Mean Square	*F*	Sig.
Intercept	2421188.921	1	2421188.921	889.365	$<.001$
Condition	218870.395	2	109435.198	40.198	$<.001$
Error	443747.828	163	2722.379		

Note: The between-subject F-test for the main effect of information quantity (condition), based on the participant-level average across complexity levels.

Table 4.14a: Robustness check. Mixed repeated-measures ANOVA. Mauchly's test of sphericity for task complexity (Self-rated mental effort)

Mauchly's Test of Sphericity[a]
Measure: `Self-rated mental effort`

Within Subjects Effect	Mauchly's *W*	Approx. Chi-Square	*df*	Sig.	Epsilon[b]		
					Greenhouse–Geisser	Huynh–Feldt	Lower-bound
ME	0.782	36.415	9	$< .001$	0.886	0.922	0.250

Note: Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

[a] Design: Intercept + Condition. Within Subjects Design: ME.
[b] May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

Note: The sphericity diagnostic for the within-subject factor (task complexity), including Greenhouse–Geisser and Huynh–Feldt epsilon values used for correction.

Table 4.14b: Robustness check. Mixed repeated-measures ANOVA. Within-subject effects of task complexity and task complexity by information quantity (Self-rated mental effort)

Tests of Within-Subjects Effects
Measure: `Self-rated mental effort`

Source		Type III Sum of Squares	*df*	Mean Square	*F*	Sig.
ME	Sphericity Assumed	60.019	4.000	15.005	11.880	$<.001$
	Greenhouse–Geisser	60.019	3.544	16.937	11.880	$<.001$
	Huynh–Feldt	60.019	3.688	16.272	11.880	$<.001$
	Lower-bound	60.019	1.000	60.019	11.880	$<.001$
ME $\times$ Condition	Sphericity Assumed	8.145	8.000	1.018	0.806	0.597
	Greenhouse–Geisser	8.145	7.087	1.149	0.806	0.584
	Huynh–Feldt	8.145	7.377	1.104	0.806	0.588
	Lower-bound	8.145	2.000	4.073	0.806	0.449
Error(ME)	Sphericity Assumed	757.839	600.000	1.263		
	Greenhouse–Geisser	757.839	531.556	1.426		
	Huynh–Feldt	757.839	553.258	1.370		
	Lower-bound	757.839	150.000	5.052		

Note: The F-tests for the within-subject main effect (task complexity) and the within-subject interaction (task complexity $\times$ information quantity/condition), reported under sphericity assumed and corrected degrees of freedom.

Table 4.14c: Robustness check. Mixed repeated-measures ANOVA. Between-subject effect of information quantity/condition (Self-rated mental effort)

Tests of Between-Subjects Effects
Measure: `Self-rated mental effort`
Transformed Variable: Average

Source	Type III Sum of Squares	*df*	Mean Square	F	Sig.
Intercept	27951.298	1	27951.298	1869.779	$<.001$
Condition	192.086	2	96.043	6.425	0.002
Error	2242.348	150	14.949		

Note: The between-subject F-test for the main effect of information quantity (condition), based on the participant-level average across complexity levels.

Table 4.15: Robustness check: Original and entropy-balanced estimates for Study 1

	IV accuracy		Trading accuracy		Mental effort	
	Original	Entropy	Original	Entropy	Original	Entropy
Intercept	0.3146	0.6046**	0.4366*	0.6753**	2.0744	-0.7168
	(1.31)	(2.12)	(1.85)	(2.45)	(1.15)	(-0.40)
Complex	-0.0668***	-0.0707***	-0.0759***	-0.0793***	0.1645***	0.1723***
	(-8.85)	(-7.74)	(-10.17)	(-8.16)	(4.61)	(3.53)
Info_Quant	-0.1214***	-0.0971***	-0.1846***	-0.1798***	0.4920***	0.5541**
	(-4.54)	(-2.87)	(-7.80)	(-6.50)	(2.62)	(2.49)
Complex × Info_Quant	-0.0424***	-0.0505***	-0.0221**	-0.0211**	0.0409	0.0230
	(-5.07)	(-5.16)	(-2.43)	(-1.98)	(0.97)	(0.42)
Risk Aversion	0.0068	-0.0174	-0.0190	-0.0297*	0.0248	0.3071**
	(0.34)	(-0.86)	(-1.12)	(-1.70)	(0.21)	(2.28)
Gender	0.0435	0.0200	0.0163	0.0130	0.6092*	0.7860**
	(0.96)	(0.42)	(0.43)	(0.29)	(1.87)	(2.43)
Fin_edu	-0.0085	0.0051	-0.0078	0.0116	0.2318	0.2802
	(-0.38)	(0.20)	(-0.32)	(0.46)	(1.53)	(1.54)
Invest_Exp	0.0634*	0.0479	0.0212	0.0038	0.4166	0.6117**
	(1.86)	(1.34)	(0.66)	(0.12)	(1.61)	(2.41)
Fin_literacy	-0.0078	-0.0015	0.0030	0.0029	0.0078	0.0170
	(-0.41)	(-0.06)	(0.16)	(0.11)	(0.08)	(0.14)
Extraversion	0.0416*	0.0440	0.0249	0.0344	-0.2236	-0.2813*
	(1.73)	(1.62)	(1.13)	(1.52)	(-1.47)	(-1.65)
Agreeableness	0.0317	-0.0006	-0.0142	-0.0433	0.1060	0.0155
	(1.13)	(-0.02)	(-0.54)	(-1.44)	(0.47)	(0.06)
Conscientiousness	-0.0007	-0.0257	0.0025	-0.0193	0.0534	-0.1337
	(-0.03)	(-0.69)	(0.09)	(-0.54)	(0.23)	(-0.51)
Neuroticism	0.0107	0.0157	0.0208	0.0237	0.2603*	0.2340
	(0.55)	(0.67)	(1.11)	(1.04)	(1.91)	(1.54)
Openness	-0.0050	-0.0133	0.0233	-0.0009	0.0647	0.7161**
	(-0.15)	(-0.31)	(0.71)	(-0.02)	(0.28)	(2.42)
Adj. R^2	0.245	0.273	0.273	0.303	0.173	0.257
Observations	830	815	830	815	805	790
Standard errors adjusted for clustering	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effect (session)	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports OLS regressions at the task level for Study 1 (Conditions 1–3). The original specifications use the full student sample. The entropy-balanced specifications are restricted to participants identifying as male or female. Female participants are reweighted to match male participants on financial education, investment experience, and financial literacy. Entropy weights are calculated at the participant level and applied consistently across the five repeated observations of each participant. Both specifications retain the original participant-level controls and session fixed effects, with standard errors clustered at the participant level. Clustered t-statistics are reported in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Chapter 5

The impact of irrelevant data on mental effort and decision quality

5.1 Study 2 motivation and design

Study 2 is motivated by a simple concern about ecological validity. In practice, investors rarely face clean, perfectly curated information sets. Instead, decision environments often mix diagnostic inputs with salient but non-diagnostic cues. Study 2 captures this feature in a controlled setting by adding two clearly irrelevant firm attributes, number of employees and R&D expenditure, while holding constant the underlying structure of the task across levels of task complexity and information quantity. Here, 'irrelevant' refers specifically to information that is non-diagnostic for the prescribed valuation task, rather than information that is necessarily irrelevant to firm value in broader financial settings

The theoretical motivation draws on cognitive-load and attention-based accounts. Cognitive Load Theory predicts that irrelevant, non-diagnostic information increases extraneous load, which can divert limited working-memory resources away from task-relevant processing and increase perceived effort (Sweller, 1988; Paas, Renkl, & Sweller, 2003; Sweller, Ayres, & Kalyuga, 2011). Related evidence from the seductive-details literature shows that adding interesting but irrelevant content can increase cognitive burden and, in some settings, reduce performance by pulling attention away from diagnostic cues (Harp & Mayer, 1998; Sanchez & Wiley, 2006; Rey, 2012; Sundararajan & Adesope, 2020). In finance, limited-attention perspectives similarly emphasise that investors do not process all available information, and that distraction and selective attention can shape price reactions and decision quality (Hirshleifer & Teoh, 2003; DellaVigna & Pollet, 2009). Despite this, much of the empirical finance evidence is observational and does not cleanly isolate irrelevance from overall information quantity, while many laboratory studies treat time and information conditions as fixed rather than examining how irrelevance interacts with the wider information environment. Study 2 addresses this gap by introducing a controlled irrelevance manipulation into an experimental valuation task while holding constant the underlying diagnostic structure. This allows a direct test of whether irrelevant cues reduce IV calculation accuracy and trading-decision accuracy, and whether they raise self-rated mental effort. It also allows these effects to vary with task complexity and information quantity, which helps identify whether irrelevance is most disruptive when the information set is sparse, or whether it remains costly even when the task is already information-dense.

The design implements this test using a between-subjects structure with six conditions. Conditions 1-3 provide the clean-information benchmark, and Conditions 4-6 add the two irrelevant fields while matching the original conditions on task complexity and information quantity. This matching means the irrelevance manipulation can be interpreted as a clean shift in the information set rather than a change in the underlying valuation problem.

The analysis proceeds from descriptive comparisons to regression specifications that exploit the repeated observations across task complexity levels. Task complexity is entered as a centred numeric trend coded -2 to $+2$ and information quantity as a centred trend coded -1 to $+1$. The regressions include session fixed effects and participant-clustered standard errors. The key specifications include the irrelevant-data indicator, its interactions with task complexity and information quantity, and the corresponding three-way interaction, before adding demographic covariates and then the Big Five traits.

5.2 Descriptive analysis

5.2.1 Balance and correlations

Study 2 extends the baseline design (Conditions 1-3) by adding irrelevant (non-diagnostic) data to the decision task. A total of 329 students participated across six conditions. Conditions 1-3 form the clean-information group ($N = 166$), and Conditions 4-6 form the irrelevant-data group ($N = 163$). The structure of the task is otherwise held constant. Conditions 4-6 match Conditions 1-3 in terms of information quantity and task complexity, with the only change being the inclusion of two additional fields, number of employees and R&D expenditure, which are not required for intrinsic value calculations. A natural first step is to compare outcomes across matched conditions before turning to the regression models that formally test main effects and moderation by task complexity and information quantity.

Table 5.1 reports that the two groups are broadly balanced on observed background characteristics and most covariates. Balance was assessed by comparing group means for each variable between the clean-information conditions (Conditions 1 to 3) and the irrelevant-data conditions (Conditions 4 to 6), using two-sample mean comparison tests reported alongside the descriptive statistics. The clearest mean difference is Agreeableness. This imbalance is unlikely to mechanically generate the load-dependent patterns shown later, since Agreeableness is not directly tied to the computational steps in the valuation task. Still, Agreeableness and the full covariate set are included in the regression specifications to ensure that irrelevant-data estimates are not confounded by small between-group differences.

Table 5.2 reports pairwise correlations among the study's participant-level control variables, including demographics and the Big Five personality traits. The bivariate associations among the demographic controls and Big Five traits are generally modest, which is reassuring from a multicollinearity perspective. The largest absolute correlations occur among some of the personality traits, consistent with the broader literature that these dimensions are related but distinct (Jiang et al., 2024).

5.2.2 Descriptive outcome patterns

Figure 5.1 compares Condition 1, low information load with clean information, to Condition 4, low information load with irrelevant data. Under low information load, irrelevant data is associated with visibly weaker performance in both tasks. IV accuracy is lower in Condition 4 than in Condition 1 at every complexity level, and the same is true for trading decision accuracy. The gap is especially apparent at lower and middle complexity levels, suggesting that when the information environment is otherwise sparse, participants may attend to the irrelevant cues and allow them to interfere with the use of the truly diagnostic inputs.

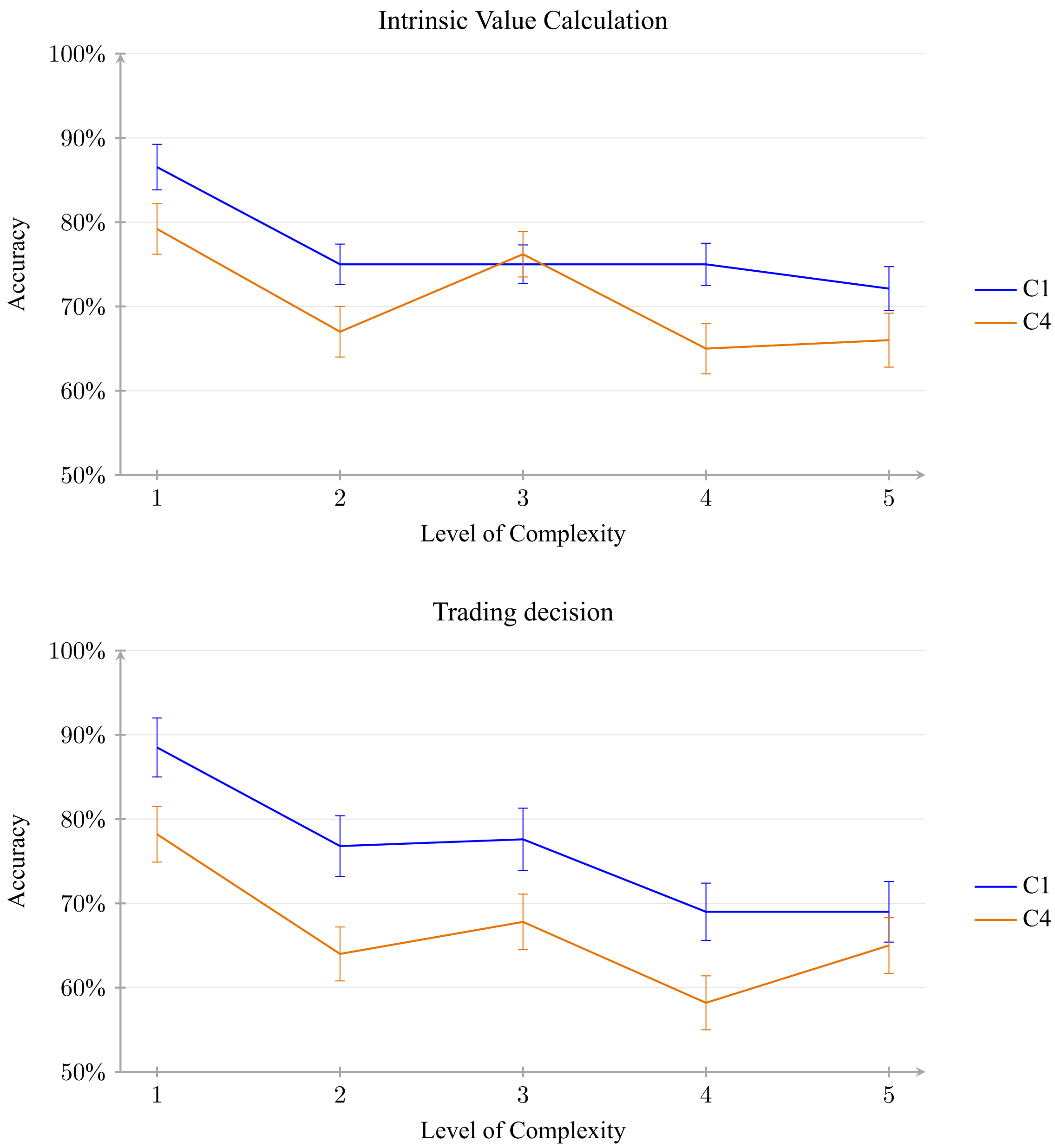

Figure 5.1: Intrinsic value calculation and trading decision accuracy (%) in Condition 1 versus Condition 4

Figure 5.2 compares Condition 2, medium information load with clean information, to Condition 5, medium information load with irrelevant data. Here the descriptive penalty from irrelevant data is much smaller. Both IV and trading accuracy decline with complexity in both conditions, but the two series are closer together, and in some places the irrelevant-data condition performs similarly to or slightly better than the clean-information benchmark.

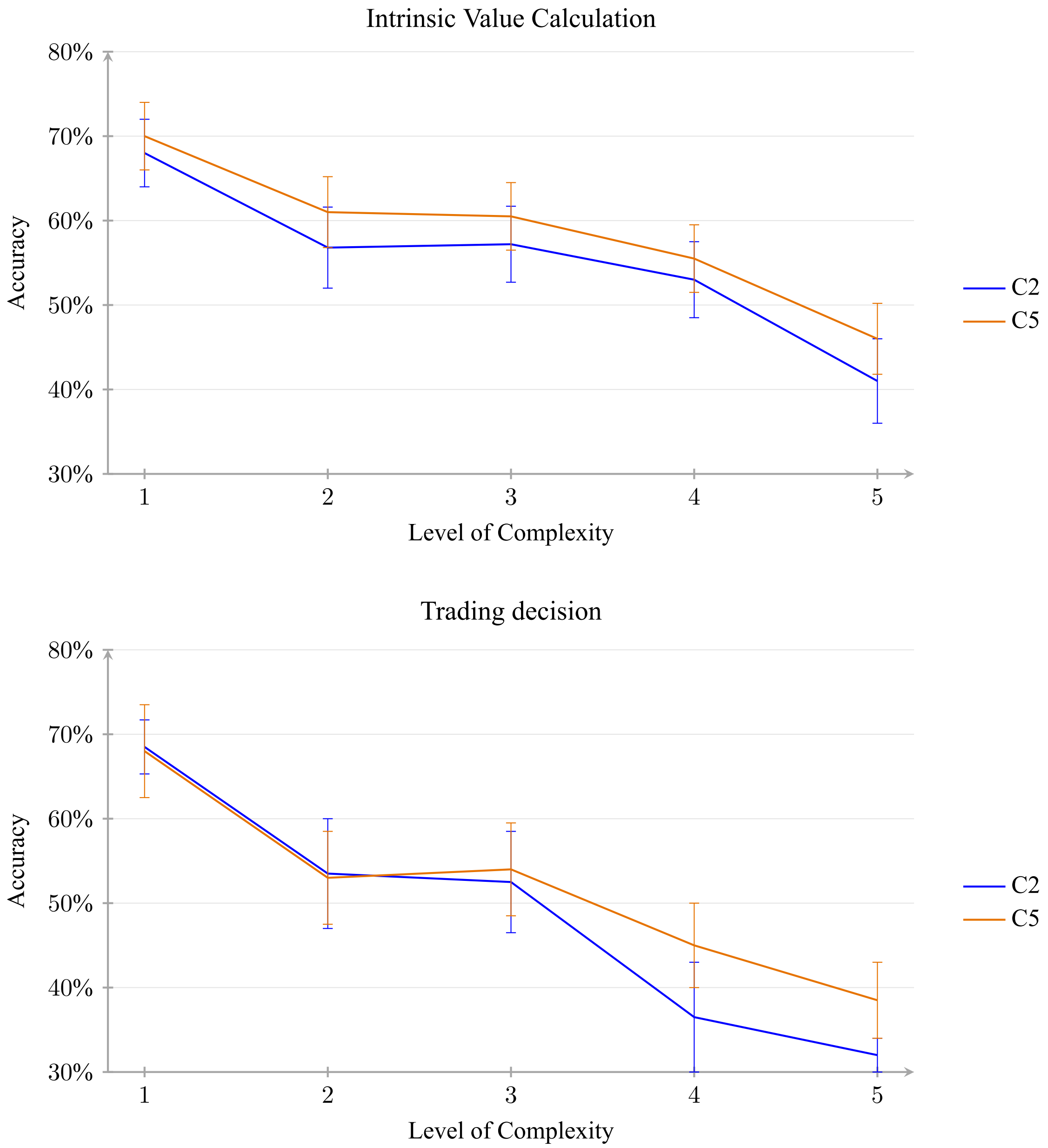

Figure 5.2: Intrinsic value calculation and trading decision accuracy (%) in Condition 2 versus Condition 5

Figure 5.3 compares Condition 3, high information load with clean information, to Condition 6, high information load with irrelevant data. Both IV and trading accuracy decline steeply with complexity in both conditions, as expected under high load. The irrelevant-data condition is similar to, and in places modestly above, the clean benchmark. Averaged across complexity levels, IV accuracy is 49.33% in Condition 3 and 51.51% in Condition 6. Trading accuracy shows a clearer gap, rising from 37.56% to 44.31%. In high-information-load settings, irrelevant data does not generate the same descriptive accuracy penalty observed under low information load.

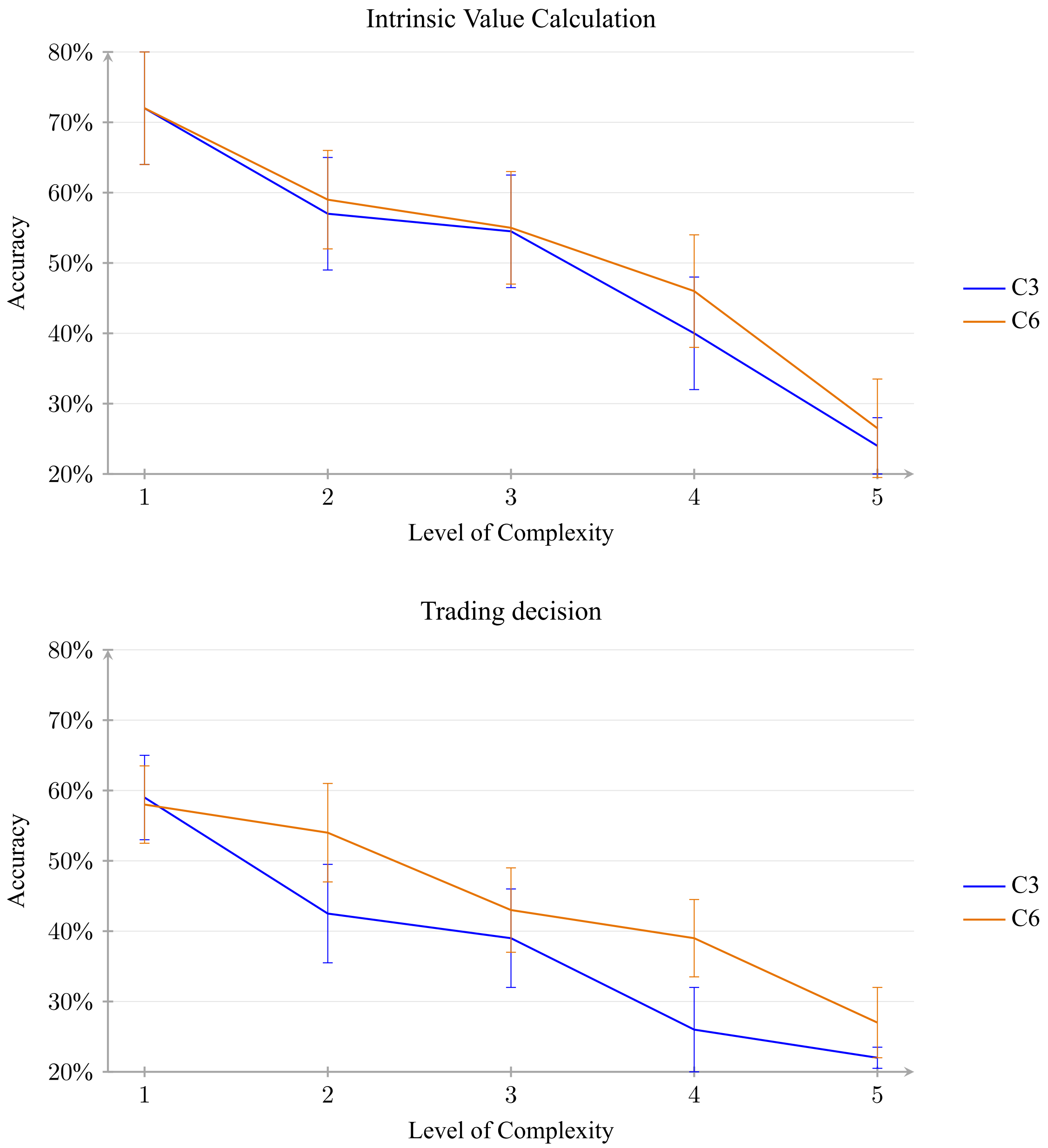

Figure 5.3: Intrinsic value calculation and trading decision accuracy (%) in Condition 3 versus Condition 6

Taken together, Figures 5.1 to 5.3 suggest that the descriptive effect of irrelevant data depends on the wider information-quantity environment. Irrelevant cues are associated with lower performance under low information load, but the difference attenuates and even reverses under medium and high information load. One plausible explanation is that irrelevant cues behave like classic distraction when the display is relatively sparse, but become easier to ignore once participants are already operating under higher task demands. This interpretation is consistent with perceptual load theory, which predicts that distractor interference is strongest under low perceptual load and tends to diminish when the primary task imposes high perceptual load (Forster & Lavie, 2009; Lavie et al., 2004; Lavie, 1995). The regression interactions test this directly by allowing the irrelevant-data effect to vary with task complexity and information quantity. This matters in the present setting because the finance evidence on distraction is largely field-based, whereas Study 2 isolates irrelevance experimentally and tests whether its costs emerge uniformly or mainly under low-load conditions.

Figure 5.4 plots mean self-rated mental effort on the 1 to 9 scale across five levels of task complexity, comparing the clean-information condition to the irrelevant-data condition within each information load. The figure provides an initial check on whether irrelevant data raises perceived workload and whether any such effect depends on the information-quantity environment.

Panel (a) compares Condition 1 to Condition 4 under low information load. Mental effort rises with task complexity in both conditions, and effort is generally higher when irrelevant data is present. Panel (b) compares Condition 2 to Condition 5 under medium information load. Effort again rises with complexity, but the gap between conditions is smaller and less uniform than under low load. Panel (c) compares Condition 3 to Condition 6 under high information load. Effort is high in both conditions and the difference between clean and irrelevant data is limited. This pattern is logically consistent with an extraneous-load interpretation. With clean information, the task remains focused on the diagnostic inputs, so participants can proceed with fewer distractions and report lower effort on average. When irrelevant cues are present under low information load, participants are more likely to notice them and expend effort screening and deciding whether they matter, which can widen the effort gap. As information quantity increases, overall workload is already high in both conditions and attention may narrow to the most diagnostic figures, so the incremental effort cost of adding a small amount of irrelevant information becomes smaller. This intuition aligns with Cognitive Load Theory, which predicts that irrelevant elements add extraneous load and increase perceived effort, and with perceptual load accounts in which distraction effects are strongest under low load and tend to diminish as task demands rise (Sweller, 1988; Paas et al., 2003; Lavie, 1995; Lavie et al., 2004).

Across the three panels, the descriptive evidence suggests a conditional effect of irrelevant data on perceived effort. Irrelevant cues appear most burdensome when the information set is sparse, while their incremental cost is smaller when the task is already information dense. The regression models below use all task-level observations, account for repeated measures by clustering at the participant level, and separate an average irrelevant-data effect from moderation by task complexity and information quantity.

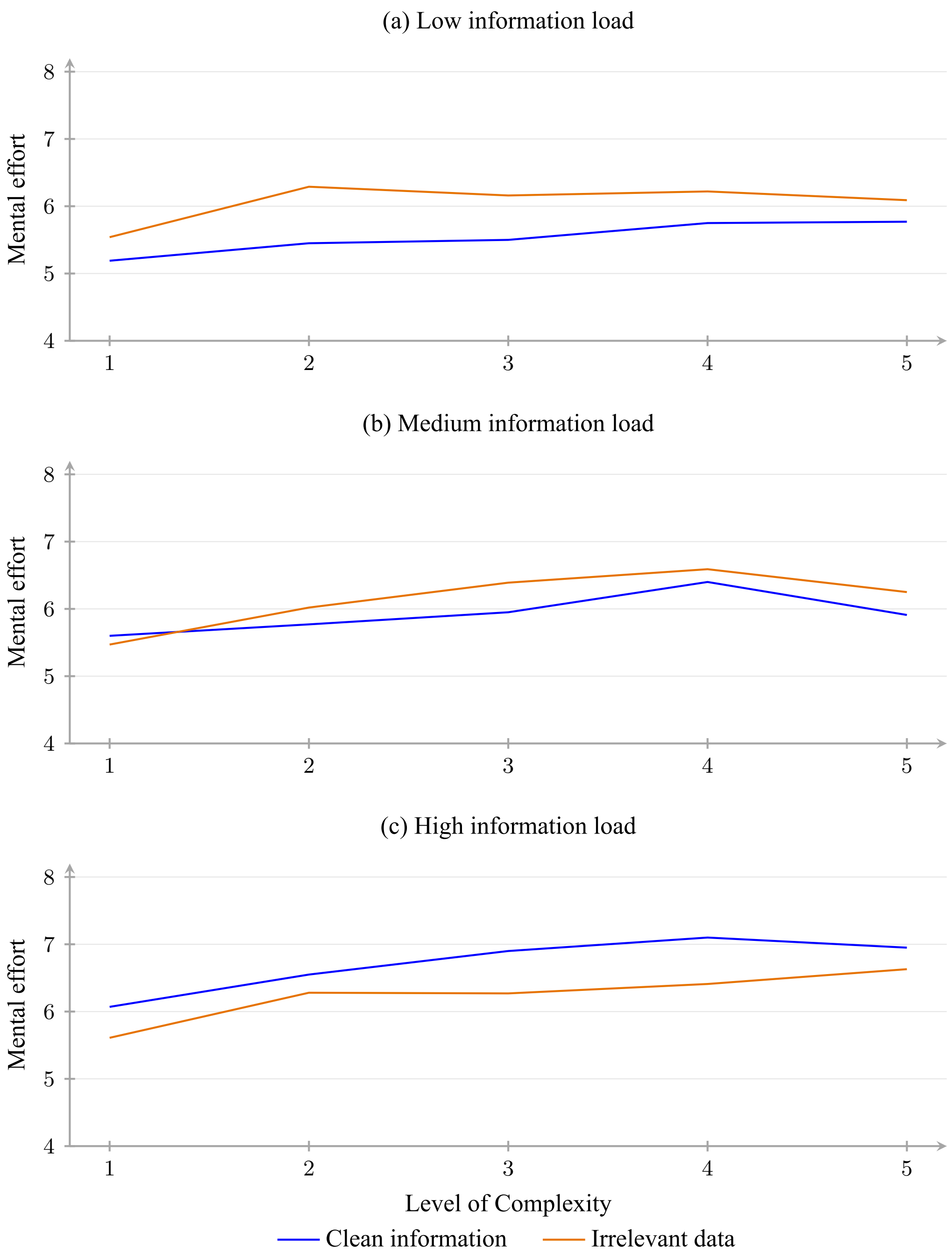

Figure 5.4: Mean self-rated mental effort by task complexity and information load.

Note: Blue lines denote the clean-information conditions (C1–C3), and orange lines denote the matched irrelevant-data conditions (C4–C6).

5.3 Regression Model

The effect of irrelevant data on decision quality and self-rated mental effort is examined by running the following regression model:

$$\begin{aligned} Y_{pi} = \alpha_1 &+ \beta_1 \mathit{Complex}_{pi} + \beta_2 \mathit{Info\_Quant}_p + \beta_3 \mathit{Irrelevant}_p \\ &+ \beta_4(\mathit{Complex}_{pi} \times \mathit{Irrelevant}_p) + \beta_5(\mathit{Info\_Quant}_p \times \mathit{Irrelevant}_p) \\ &+ \beta_6(\mathit{Complex}_{pi} \times \mathit{Info\_Quant}_p) \\ &+ \beta_7(\mathit{Complex}_{pi} \times \mathit{Info\_Quant}_p \times \mathit{Irrelevant}_p) + \gamma X_p + \varepsilon_{pi} \end{aligned}$$

where Y_{pi} denotes decision quality (the percentage correct in intrinsic value calculations and trading decisions) or self-rated mental effort for participant p at the task-complexity level i. Task complexity is coded as a centred numeric trend, $\mathit{Complex} \in \{-2, -1, 0, 1, 2\}$ for levels 1-5 (0 corresponds to level 3), and information quantity is coded as $\mathit{Info\_Quant} \in \{-1, 0, 1\}$ for levels 1-3 (0 corresponds to level 2). *Irrelevant* is a dummy variable that takes the value 1 if irrelevant data is included in the questions and 0 otherwise. X_p is a vector of between-subject controls[7] (gender, financial education, experience, financial literacy, risk tolerance, and the Big Five traits), and standard errors are clustered by participant to account for repeated observations across complexity levels. The coefficient β_1 measures the change in the correct percentage for a one-step increase in task complexity at $\mathit{Info\_Quant} = 0$ (the medium information-quantity baseline), holding control variables fixed, while the coefficient β_2 captures the change in the correct percentage for a one-step increase in information load at task complexity level 3. The coefficient β_3 captures the average change in the outcome associated with the presence of irrelevant data, holding other variables constant.

The coefficients β_4 and β_5 capture how the effect of irrelevant data varies with the task environment. These interaction terms are included because the irrelevance manipulation is not expected to operate as a simple level shift. Instead, theories of limited attention and cognitive load imply that the marginal cost of irrelevant cues can depend on how demanding the task already is.

The coefficient β_4 on *Irrelevant* × *Complex* tests whether irrelevant cues become more or less disruptive as tasks require more computation. If higher complexity consumes more working-memory resources, participants may have less capacity to process irrelevant information, which would imply a weaker irrelevance effect at high complexity. Alternatively, if complexity already strains capacity, irrelevant cues could further increase confusion or misweighting, which would imply a stronger irrelevance effect as complexity rises. β_4 therefore tells us whether irrelevant information changes the complexity slope, rather than shifting outcomes by a constant amount.

The coefficient β_5 on *Irrelevant* × *Info_Quant* plays an analogous role for the amount of information shown. When information quantity is low, irrelevant cues may be more salient and receive attention because the display is otherwise sparse, which could make them more harmful. When information quantity is high, irrelevant cues may be crowded out by the diagnostic information and therefore contribute little additional disruption, or they may worsen overload if participants attempt to process everything. β_5 therefore tests whether the irrelevance effect is concentrated in low-information-quantity environments

[7] Since all participants are in the same age group, age is not included in the control variables set.

or persists, or even grows, as the information set becomes dense.

The coefficient β_6 measures how the complexity slope changes as the quantity of information increases, and the higher-order interaction term β_7 tests whether irrelevant cues alter the way complexity and information quantity jointly shape performance and effort, which is the most direct specification for evaluating whether irrelevance acts as extraneous load and whether its impact depends on broader task demands.

5.4 Regression results

5.4.1 Robustness of Study 1 Results

Before examining irrelevant-data effects, I re-estimate the baseline load relationships using only Conditions 4-6, which all contain the irrelevant fields. This provides a check that the basic task mechanics are preserved once non-diagnostic cues are present. These regressions use the same task-level structure as the main models, including session fixed effects and participant-clustered standard errors.

Table 5.3 reports that IV calculation accuracy declines with both task complexity and information quantity within the irrelevant-data sample, and that the complexity-by-information-quantity interaction is negative. In column (3), a one-step increase in task complexity is associated with a 5.80 percentage point decline in IV accuracy, and a one-step increase in information quantity is associated with a 10.02 percentage point decline. Given a mean IV accuracy of the irrelevant-data sample is 60%, these estimates correspond to declines of roughly 9.62% and 16.61% relative to that baseline. The interaction term implies that the complexity penalty steepens by about 3.13 percentage points for each additional step of information quantity. The key coefficients remain similar after adding controls in columns (4) and (5).

This replication is useful because it shows that adding irrelevant cues does not fundamentally change the demand structure of the task. It supports treating the later irrelevant-data results as a change in the information environment, not a change in what the task is asking participants to do.

Table 5.4 shows that trading-decision accuracy follows the same pattern as IV accuracy. Both task complexity and information quantity are significantly negative, while the interaction is negative but less significant than in the IV models. Accordingly, in column (3), the quality of trading decisions falls by around 5.53 percentage points and 11.46 percentage points for each one-step increase in task complexity and information quantity, respectively, while each additional step of information quantity increases the complexity-related loss by roughly 1.78 percentage points. These main effects remain strong and stable in columns (4) and (5). The interaction remains negative and approximately the same magnitude, but is statistically significant only at the 10% level. A couple of controls show weak signals, for example, financial education is positive and Neuroticism is negative in column (5), but again they do not explain away the main effects. These results are broadly consistent with those from Conditions 1-3 in sign and magnitude, with trading decisions deteriorating as tasks become more complex and as more information is presented. The mild difference is that the interaction is weaker here than for IV accuracy, and weaker than in the full clean-information sample, which fits the idea that trading choices embed additional noise or strategy variation on top of calculation skill.

In Table 5.5, self-rated mental effort increases sharply with task complexity, whereas the incremental contribution of information quantity, and the *Complex* $\times$ *Info_Quant* interaction, within the irrelevant-data sample is comparatively weak. This pattern is unchanged when demographic and personality controls are added in columns (4) and (5), indicating that the complexity effect is not driven by observable differences in participant characteristics. The dominance of complexity in perceived workload is consistent with cognitive-load accounts, which hold that increases in intrinsic task demands reliably elevate experienced effort (Sweller, 1988; Paas et al., 2003; Sweller et al., 2011). Several controls also show behaviourally plausible associations with effort ratings. Investment experience, measured as years trading stocks, is positively related to reported effort. Although experience can, in principle, make information processing more efficient and potentially lower perceived effort, the positive association observed here is more consistent with an effort-investment or engagement interpretation, in which experienced participants choose to process more thoroughly rather than relying on automatic, routinised responses. This result aligns with evidence that investing experience is associated with differences in information engagement and search or stopping behaviour among nonprofessional investors (Elliott et al., 2008; Loibl & Hira, 2009; Pennington & Kelton, 2016). Conscientiousness is likewise positively associated with effort, consistent with research linking Conscientiousness to greater effort investment and persistence (Rieger et al., 2022; Van Iddekinge et al., 2023). Neuroticism also shows a positive association, which accords with theories and evidence indicating that higher Neuroticism is associated with greater reactivity under demanding conditions and higher perceived strain (Eysenck et al., 2007). Taken together, these covariate patterns suggest that participants who are more engaged or more affectively reactive tend to report higher effort, but the headline remains that task complexity is the only consistently strong experimental driver of perceived effort in this subsample.

Across Tables 5.3-5.5, the irrelevant-data subsample reproduces the main structural relationships found in the clean-information sample. Decision quality declines with higher complexity and higher information quantity, and perceived effort rises with complexity. This sets the stage for the central Study 2 test, which compares clean versus irrelevant displays and examines whether irrelevance shifts outcomes on average or mainly through load-dependent moderation.

5.4.2 Study 2 results

Main effect of irrelevant data

If irrelevant cues mainly add extraneous load, they should reduce decision quality and increase perceived effort. Table 5.6 reports that the irrelevant-data coefficient for IV calculation accuracy is negative in every specification. In the full-controls column, the coefficient on irrelevant data is -0.0467, implying about a 4.67 percentage point lower IV accuracy at the centred reference point[8]. The corresponding t-value is -1.60, so this average effect is statistically insignificant.

Table 5.7 reports a similar pattern for trading-decision accuracy, but with a smaller magnitude. In the full-controls column, the coefficient on irrelevant data is -0.0284, or about a 2.84 percentage point

[8] In Tables 5.6-5.8, task complexity is entered as a centred numeric trend coded from -2 to $+2$, and information quantity is coded from -1 to $+1$. Irrelevant data is an indicator equal to 1 when the two irrelevant fields are shown. Because the trends are centred, the irrelevant-data coefficient is interpreted at the benchmark setting where *Complex* $= 0$ and *Info_Quant* $= 0$, which corresponds to the middle complexity level and the medium-information condition. The interaction terms indicate whether the irrelevant-data effect varies with task complexity or information quantity. All models include session fixed effects and participant-clustered standard errors.

decline at the centred reference point. The corresponding t-value is -1.02, so this average effect is statistically insignificant.

I next examine whether the same load-dependent pattern appears in perceived workload. Table 5.8 reports clearer evidence for self-rated mental effort. In the full-controls column, the irrelevant-data coefficient is 0.327, indicating about a 0.33-point increase on the 1-9 effort scale. The corresponding t-value is 1.70, which is significant at the 10% level. The estimate is similar when demographic controls are introduced, where the coefficient is 0.350 with a t-value of 1.78. In practical terms, irrelevant cues increase perceived effort even when average accuracy effects are modest and statistically insignificant.

A simple reconciliation is that participants partly compensate for the added noise. They report higher effort when irrelevant cues are present, which is consistent with additional screening or double-checking, while average accuracy changes remain small once complexity and information quantity are controlled for.

Interactions and load dependence

A sharper test of irrelevance as distraction is whether its impact depends on the task environment. It should be most harmful when the task is light enough for attention to drift toward nondiagnostic cues, and less harmful when cognitive demands are already high.

For IV calculation accuracy, Table 5.6 shows little evidence that the irrelevance effect varies systematically with task demands. In the full-controls specification, the *Irrelevant* $\times$ *Complex* coefficient is 0.0088 with a t-value of 0.83, the *Irrelevant* $\times$ *Info_Quant* coefficient is 0.0080 with a t-value of 0.22, and the three-way interaction *Irrelevant* $\times$ *Complex* $\times$ *Info_Quant* is 0.0111 with a t-value of 0.93. All of these moderation terms are statistically insignificant, implying that any average irrelevance penalty for IV accuracy does not concentrate in particular load combinations.

Table 5.7 reports more meaningful heterogeneity for trading-decision accuracy. The coefficients in the full-controls column show that the main irrelevant-data effect at the centred reference point is modest and statistically insignificant, but that this effect varies with task load through two positive, marginally significant interaction terms, *Irrelevant* $\times$ *Complex* $= 0.0207$ ($t = 1.91$) and *Irrelevant* $\times$ *Info_Quant* $= 0.0566$ ($t = 1.76$), while the three-way interaction is statistically insignificant (0.0043, $t = 0.33$). Because task complexity is coded from -2 to $+2$ and information quantity from -1 to $+1$, the marginal effect of irrelevant data at any load combination is $\beta_3 + \beta_4\, \textit{Complex} + \beta_5\, \textit{Info\_Quant} + \beta_7\, (\textit{Complex} \times \textit{Info\_Quant})$. Evaluated at the lowest-load combination (*Complex* $= -2$; *Info_Quant* $= -1$), this implies an effect of approximately -11.8 percentage points. This can be decomposed into the midpoint effect of -2.8 percentage points, plus -4.1 percentage points from the *Irrelevant* $\times$ *Complex* term and -5.7 percentage points from the *Irrelevant* $\times$ *Info_Quant* term, partly offset by about 0.9 percentage points from the three-way term. At the midpoints, where *Complex* $= 0$ and *Info_Quant* $= 0$, the effect collapses to the main Irrelevant coefficient of about -2.8 percentage points. At the highest-load combination, where *Complex* $= 2$ and *Info_Quant* $= 1$, the same decomposition yields an implied effect of about $+7.8$ percentage points, reflecting positive contributions of roughly $+4.1$ percentage points from *Irrelevant* $\times$ *Complex*, $+5.7$ percentage points from *Irrelevant* $\times$ *Info_Quant*, and $+0.9$ percentage points from the three-way term that together outweigh the negative midpoint effect. The key takeaway is therefore the gradient. Irrelevant cues appear most damaging in low-load settings and progressively less damaging as complexity and information quantity increase. This pattern fits a spare-capacity account, in which attention drifts toward nondiagnostic lines when tasks are light, whereas under high load participants narrow focus to the most diagnostic cues.

Table 5.8 suggests that the effort cost of irrelevance depends more on information quantity than on complexity. In the full-controls column, the *Irrelevant* $\times$ *Info_Quant* coefficient is -0.3073 with a t-value of -1.28, and the *Irrelevant* $\times$ *Complex* coefficient is 0.0112 with a t-value of about 0.2, so both interaction terms are statistically insignificant in that specification. However, Table 5.8 also reports a more negative *Irrelevant* $\times$ *Info_Quant* coefficient in columns (2)-(4), around -0.43 with t-values near -1.8 and significant at the 10% level. Translating the full-controls coefficients into model-implied effects provides a descriptive summary. The implied effort premium from irrelevant cues is about 0.63 points at low information load (*Info_Quant* $= -1$) across most complexity levels, about 0.33-0.35 points at the midpoint (*Info_Quant* $= 0$), and close to 0 to $+0.07$ points at high information load (*Info_Quant* $= 1$) for moderate-to-high complexity. In other words, irrelevant information is experienced as more burdensome when the information set is sparse to moderate, but its incremental perceived cost becomes small once the information environment is already dense. Because the full-controls model is the preferred specification, I interpret the evidence for an information-dependent irrelevance effect on effort as suggestive rather than conclusive.

5.5 Results discussion

Study 2 examines whether adding clearly nondiagnostic firm information (R&D expenditure and number of employees) would impair decision quality and increase perceived mental effort, beyond the effects of task complexity and information quantity. The design was motivated by Cognitive Load Theory, which treats such information as extraneous load that consumes limited working-memory resources without improving task performance (Sweller, 1988; Paas et al., 2003; Sweller et al., 2011). In the multimedia and text-learning literature, similar "seductive details" reliably make tasks feel harder and often reduce learning, especially when they are interesting but irrelevant to the learning goal (Harp & Mayer, 1998; Sanchez & Wiley, 2006; Rey, 2012; Schneider et al., 2018; Sundararajan & Adesope, 2020). In a financial judgment setting, this literature suggests that adding irrelevant lines to an already demanding valuation task should divert attention away from diagnostic items and increase cognitive strain.

Consistent with prior work on information load and task complexity in accounting and decision-making (Jacoby, 1984; Schick et al., 1990; Eppler & Mengis, 2004; Payne J. W., 1976; Hartmann & Weißenberger, 2024), task complexity and information quantity remain the dominant drivers of performance in Study 2. IV accuracy and trading accuracy both decline steeply as tasks become more complex and as more information is provided, and the interaction between complexity and information quantity is negative for trading decisions, indicating that these dimensions compound one another. Once task complexity and information quantity are accounted for, the average impact of irrelevant information on accuracy is modest and statistically insignificant. At the centred reference point (mid-complexity and mid-information), the presence of irrelevant cues is associated with roughly a 3.5-4.7 percentage point lower IV accuracy and a 2.2-2.8 percentage point lower trading accuracy, but the corresponding coefficients are not statistically significant once complexity and information quantity are controlled for. In other words, participants were able to protect most of their calculation and trading performance from a relatively light irrelevance manipulation when facing already demanding tasks.

The interaction patterns qualify this picture for trading decisions and link back to several strands of prior work on irrelevance. First, this pattern is consistent with compensatory behaviour. In interruption research, participants reduce errors by adopting a more cautious resumption strategy, often at the cost of greater time or effort, reflecting an explicit speed–accuracy trade-off (Brumby et al., 2013). In the present setting, irrelevant cues may trigger a similar response, participants may invest extra effort in screening or checking, which can dampen average accuracy losses even though the task feels more demanding. Furthermore, in auditing experiments, seemingly irrelevant information can dilute cue weighting and impair judgment, but time pressure and accountability sometimes push auditors to focus more on core evidence (Hackenbrack, 1992; Glover, 1997; Shelton, 1999). In corporate reporting, longer, more redundant, or obfuscated disclosures appear to hinder processing and, in some settings, reallocate investor attention in ways that reduce the usefulness of accounting information (Ertugrul et al., 2017; deHaan et al., 2021; Dyer et al., 2017; Hartmann & Weißenberger, 2024). Recent work on conference calls shows that irrelevant answers can similarly distort analysts' forecasts and investors' reactions (Wang et al., 2024; Hao et al., 2025). In Study 2, the marginal effect of irrelevant information on trading accuracy appears most negative in relatively simple, low-information tasks, and tends to attenuate as complexity and information quantity increase. Under low-complexity/low-information-quantity conditions, model predictions imply accuracy penalties on the order of 10 percentage points when irrelevant cues are present, whereas at mid-range difficulty, the estimated penalty shrinks to only a few percentage points, and under the most complex, information-rich conditions, the net effect is close to zero and may even become weakly positive. These interaction terms are only marginally significant and should be interpreted cautiously; however, they echo Lavie's (1995) perceptual load account, which suggests that irrelevant stimuli are most disruptive when the relevant load is still low enough to allow spare attentional capacity. Once intrinsic and informational load are high, additional nondiagnostic items largely behave as background noise. This pattern also aligns well with limited-attention explanations of investor behavior, where distraction and selective processing are strongly context-dependent (Hirshleifer & Teoh, 2003; DellaVigna & Pollet, 2009; Hirshleifer et al., 2011; Tetlock, 2011).

The mental-effort results provide clearer support for an extraneous-load interpretation. A complementary interpretation is that higher effort reflects a deliberate attempt to stabilise performance. Brumby et al. (2013) show that when task resumption is disrupted, slower, more reflective behaviour reduces errors, implying a speed–accuracy trade-off. This offers a plausible behavioural parallel here. Participants may experience higher effort because they engage in additional checking to offset the presence of nondiagnostic cues. After controlling for task complexity and information quantity, irrelevant information is associated with a moderate and robust increase in self-rated effort of about 0.33 to 0.35 points on the 1 to 9 scale, and this effect persists after demographic and personality controls are included. This pattern is consistent with cognitive-load accounts in which irrelevant material consumes limited working-memory resources without contributing to productive processing (Sweller J. , 1988; Paas & Merriënboer, 1993). It also accords with the seductive-details literature, which shows that irrelevant but interesting material can impair learning by diverting attention and burdening cognitive processing (Harp & Mayer, 1998; Rey, 2012), particularly for learners with lower working-memory capacity (Sanchez & Wiley, 2006). Because evidence on subjective load ratings in that literature is mixed, the present findings are best viewed as extending earlier work by showing a clearer perceived-effort effect in a financial decision setting. The negative and marginally significant interaction between irrelevance and information quantity further suggests that this effort penalty is most evident when the information set is relatively sparse and diminishes as the display becomes denser.

Taken together, the results of Study 2 suggest that the irrelevance manipulation primarily acts as a mild source of additional cognitive load rather than a major driver of performance breakdown. Irrelevant information reliably increases perceived effort, especially at lower information quantities, and may harm accuracy in simpler, low-information tasks. However, its average impact on IV and trading accuracy is modest compared to the strong and robust effects of complexity and information quantity. This adds nuance to the dilution and seductive-details literatures in both psychology and applied finance. When nondiagnostic content is quantitative, clearly labelled, and relatively sparse, and when decision makers are working under time constraints, they seem able to screen out most of the potential damage to accuracy (Hackenbrack, 1992; Glover, 1997; Eitel et al., 2019; Wang et al., 2024; Hao et al., 2025), while still incurring a modest but noticeable increase in perceived mental effort.

One possible explanation for the attenuation of the irrelevant-data effect at higher information loads is a shift toward more selective information processing. Research on selective attention suggests that the extent to which irrelevant stimuli are processed depends on the demands imposed by the focal task. Load theory, for example, proposes that when relevant processing consumes a larger share of available attentional capacity, fewer resources may remain available for processing peripheral distractors (Lavie, 2005, 2010). More recent evidence also indicates that demanding tasks can reduce the processing of irrelevant stimuli (Brockhoff et al., 2022). In lower-load environments, by contrast, spare attentional capacity may "spill over" to information that is not necessary for the task. This provides a possible explanation for the present pattern. When the information environment is relatively sparse, participants may have sufficient attentional capacity to inspect the additional R&D and employee information even though these cues are not diagnostic. As the core task becomes more demanding, participants may increasingly prioritise the valuation inputs required for the calculation and allocate less attention to the irrelevant fields.

This interpretation is also consistent with evidence that the processing of irrelevant information depends on attentional control and task conditions. Sanchez and Wiley (2006) show that individuals with lower working-memory capacity attend more frequently and for longer to irrelevant material, suggesting that stronger attentional control helps individuals suppress non-diagnostic information. In auditing, Glover (1997) similarly finds that time pressure reduces the dilution effect of nondiagnostic evidence, which has been interpreted as greater filtration and concentration on more diagnostic cues. Applied to the present experiment, participants facing high information quantity may adopt a more restrictive processing strategy in which clearly unnecessary fields are screened out earlier. This would reduce the incremental cost of irrelevant information even though the underlying task remains difficult. However, this mechanism is inferred rather than directly observed. Because the experiment does not track visual attention or information search, the selective-filtering explanation should be treated as a plausible interpretation rather than a direct test of attentional filtering

These results provide clearer support for H3b than for H3a. H3b predicted that irrelevant information would increase perceived mental effort, and consistent with this, irrelevance is associated with a modest but robust increase in self-rated effort. H3a predicted that irrelevant information would reduce decision quality. The estimates are directionally consistent with this prediction for both IV calculations and trading decisions, since the point estimates at the centred reference point are negative, but the average effects are generally small and statistically insignificant once task complexity and information quantity are controlled for. The trading interactions nonetheless suggest a meaningful boundary condition. Any irrelevance penalty appears concentrated in simple, low-information-quantity environments, while it largely attenuates under high complexity and high information load. Overall, Study 2 indicates that irrelevant information primarily raises perceived effort, whereas its average effect on objective accuracy is modest and appears most evident under lower-load conditions.

5.6 Robustness check

To assess whether the main results are driven by a small group of very weak performers, I re-estimate the models on a restricted sample that excludes any participant who ever recorded 0% IV accuracy at any complexity level. Table 5.9 indicates that the core relationship between task complexity and information quantity remains essentially unchanged. In the full-controls specification, the complexity coefficient remains about -0.07 and the information quantity coefficient remains about -0.13, and the *Complex* × *Info_Quant* interaction remains strongly negative. Table 5.10 reports a similar pattern for trading decisions, with complexity around -0.08, information quantity around -0.18, and a negative *Complex* × *Info_Quant* interaction around -0.046. The fit also remains comparable, with adjusted R^2 rising from about 0.15 in column (1) to about 0.40 in column (5) for IV accuracy, and around 0.30 in the richer trading specifications. These patterns indicate that the primary complexity and information effects are not an artefact of disengaged participants.

The robustness estimates also refine the conclusions about irrelevant information. For IV calculation accuracy, the magnitude of the irrelevance effect is very similar to that in the main analysis, but the restricted sample reduces the standard errors. In Table 5.6 for the full sample, the *Irrelevant* coefficient in the richest IV model was about -0.0467; in Table 5.9 for the restricted sample, it was -0.0399, statistically significant at the 5% level. This supports the claim that irrelevant lines do exert a small but genuine penalty on IV calculation accuracy, in addition to the much larger effects of complexity and information load. For trading decisions, the average irrelevance effect remains small and statistically indistinct from zero, but the *Irrelevant* × *Complex* interaction becomes more clearly significant. The full-sample estimates already suggest a positive interaction of about 0.0207 in Table 5.7. In Table 5.10 for the restricted sample, this rises to 0.0286 and is statistically significant at the 5% level, reinforcing the interpretation that irrelevant cues are most disruptive when the task is relatively simple and are largely screened out once complexity is high. For mental effort, the direction of the irrelevance effect remains positive, but its size and significance drop. The main-sample models in Table 5.8 indicate an increase of roughly 0.33 points on the 1-9 scale, whereas in Table 5.11 for the restricted sample, the corresponding coefficient is only about 0.10 and statistically insignificant. This suggests that the extra effort required to process irrelevant information is concentrated among participants who struggled most with the IV calculations. In general, the robustness checks show that irrelevant information behaves as a small but non-trivial perturbation. They tighten the evidence for a modest accuracy penalty in IV calculations and for a more conditional interaction pattern in trading decisions, without altering the central conclusion that task complexity and information quantity remain the dominant determinants of both performance and perceived effort in Study 2.

As an additional robustness check, I repeat the entropy-balancing procedure described in Study 1 for the Study 2 sample. Female participants are reweighted to match male participants on financial education, investment experience, and financial literacy, while the original session fixed effects, participant controls, and participant-clustered standard errors are retained. The principal results in Table 5.12 remain qualitatively consistent with the original estimates. In particular, the strong effects of task complexity and information quantity remain stable, while the overall conclusion regarding irrelevant information is unchanged. Although some secondary interaction coefficients vary in statistical significance, these differences do not alter the substantive interpretation of Study 2.

Table 5.1: Descriptive statistics.

	Condition 123 ($N = 166$)					Condition 456 ($N = 163$)					Test of Difference in			
Variable	Mean	Median	Stdev	Min	Max	Mean	Median	Stdev	Min	Max	Mean	p-value	Median	p-value
Risk Aversion	2.325	2.000	1.057	1.000	4.000	2.442	2.000	1.019	1.000	4.000	-0.116	0.310	0.000	0.312
Age	1.006	1.000	0.078	1.000	2.000	1.037	1.000	0.399	1.000	6.000	-0.031	0.335	0.000	0.550
Gender	1.753	2.000	0.498	1.000	4.000	1.791	2.000	0.451	1.000	4.000	-0.038	0.464	0.000	0.401
Financial Education	2.747	3.000	0.879	1.000	6.000	2.724	3.000	0.848	1.000	6.000	0.023	0.809	0.000	0.932
Investment experience	1.367	1.000	0.575	1.000	4.000	1.337	1.000	0.558	1.000	4.000	0.030	0.631	0.000	0.620
Financial Literacy	4.006	4.000	1.098	0.000	5.000	4.012	4.000	1.024	1.000	5.000	-0.006	0.957	0.000	0.867
Extraversion	3.670	3.750	0.898	1.000	6.000	3.735	3.750	0.846	1.250	6.000	-0.064	0.503	0.000	0.419
Agreeableness	4.554	4.750	0.817	1.000	6.000	4.744	4.750	0.639	2.500	6.000	-0.190	0.020**	0.000	0.083
Conscientiousness	4.212	4.250	0.770	2.250	6.000	4.304	4.250	0.733	1.750	6.000	-0.091	0.271	0.000	0.381
Neuroticism	4.175	4.250	1.012	1.250	6.000	4.333	4.500	0.949	2.250	6.000	-0.158	0.145	-0.250	0.171
Openness	4.349	4.500	0.766	1.000	6.000	4.396	4.500	0.803	2.250	6.000	-0.046	0.593	0.000	0.818

Note: Table 5.1 summarises participant characteristics for the clean-information group (conditions 1-3) and the irrelevant-data group (conditions 4-6). For each variable, this table reports the mean, median, standard deviation, minimum, and maximum by group. The final columns quantify between-group differences, with the mean difference computed as (conditions 1-3) − (conditions 4-6), along with two-sided p-values for tests of equality of means and medians.

Table 5.2: Correlation matrix.

		1	2	3	4	5	6	7	8	9	10	11
1	Risk Aversion	1										
2	Age	0.106	1									
3	Gender	-0.292**	0.238**	1								
4	Financial Education	-0.016	0.171**	0.158**	1							
5	Investment experience	0.148**	0.255**	-0.245**	-0.096	1						
6	Financial Literacy	0.116*	0.029	-0.123*	0.039	0.167**	1					
7	Extraversion	0.117*	-0.030	-0.008	-0.077	0.023	0.070	1				
8	Agreeableness	-0.083	-0.033	-0.001	-0.118*	0.008	0.111*	0.230**	1			
9	Conscientiousness	-0.152**	-0.075	-0.051	-0.171**	-0.019	-0.017	0.043	0.348**	1		
10	Neuroticism	-0.113*	0.076	0.237**	0.090	-0.113*	-0.026	-0.089	0.164**	-0.064	1	
11	Openness	0.143**	0.077	-0.138*	-0.025	0.116*	0.081	0.291**	0.316**	0.319**	-0.041	1

Note: This table reports pairwise correlations among the study's participant-level control variables ($N = 329$).

Table 5.3: Task Complexity and Information Quantity Predict IV Calculation Accuracy (conditions 4-6)

	(1)	(2)	(3)	(4)	(5)
Intercept	0.6333^{***}	0.6565^{***}	0.6565^{***}	0.7366^{***}	1.0150^{***}
	(8.72)	(10.90)	(10.88)	(4.89)	(4.58)
Complex	-0.0590^{***}		-0.0580^{***}	-0.0580^{***}	-0.0580^{***}
	(-7.56)		(-7.68)	(-7.66)	(-7.64)
Info_Quant		-0.1002^{***}	-0.1002^{***}	-0.0984^{***}	-0.1049^{***}
		(-3.88)	(-3.88)	(-3.73)	(-3.92)
Complex × Info_Quant			-0.0313^{***}	-0.0313^{***}	-0.0313^{***}
			(-3.66)	(-3.65)	(-3.64)
Risk Aversion				-0.0194	-0.0113
				(-0.89)	(-0.50)
Gender				-0.0500	-0.0262
				(-0.96)	(-0.48)
Fin_edu				-0.0021	-0.0116
				(-0.09)	(-0.54)
Invest_Exp				-0.0200	-0.0185
				(-0.50)	(-0.47)
Fin_literacy				0.0228	0.0214
				(0.99)	(0.96)
Extraversion					-0.0376
					(-1.46)
Agreeableness					0.0390
					(1.28)
Conscientiousness					0.0168
					(0.58)
Neuroticism					-0.0436^{*}
					(-1.82)
Openness					-0.0655^{**}
					(-2.23)
Adj. R^2	0.082	0.072	0.135	0.138	0.164
Observations	815	815	815	815	815
Standard errors adjusted for clustering	Individual	Individual	Individual	Individual	Individual
Fixed effect (session)	Yes	Yes	Yes	Yes	Yes

Note: The table reports OLS regressions at the task level. Predictors are entered as centred numeric trends. All models include session fixed effects, and inference is based on participant-clustered (cluster-robust) t-statistics reported in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. The dependent variable is participants' intrinsic-value (IV) calculation accuracy, estimated using the irrelevant-data sample only (conditions 4-6; $N = 163$). Column (1) includes only the task complexity trend. Column (2) includes only the information quantity trend. Column (3) includes both trends and their interaction (Complex × Info_Quant). Column (4) adds demographic covariates. Column (5) further includes the Big Five personality traits.

Table 5.4: Task Complexity and Information Quantity Predict Trading-Decision Accuracy (Conditions 4–6)

	(1)	(2)	(3)	(4)	(5)
Intercept	0.5526***	0.5790***	0.5790***	0.7460***	0.8215***
	(7.81)	(9.51)	(9.50)	(4.87)	(3.58)
Complex	-0.0558***		-0.0553***	-0.0553***	-0.0553***
	(-7.04)		(-7.03)	(-7.01)	(-6.99)
Info_Quant		-0.1146***	-0.1146***	-0.1096***	-0.1096***
		(-5.01)	(-5.00)	(-4.67)	(-4.52)
Complex × Info_Quant			-0.0178*	-0.0178*	-0.0178*
			(-1.90)	(-1.90)	(-1.89)
Risk Aversion				0.0009	0.0067
				(0.05)	(0.34)
Gender				-0.0633	-0.0351
				(-1.37)	(-0.73)
Fin_edu				0.0459**	0.0399*
				(2.28)	(1.95)
Invest_Exp				-0.0067	-0.0051
				(-0.18)	(-0.14)
Fin_literacy				0.0248	0.0240
				(1.26)	(1.24)
Extraversion					-0.0169
					(-0.78)
Agreeableness					0.0144
					(0.46)
Conscientiousness					0.0312
					(1.09)
Neuroticism					-0.0340*
					(-1.75)
Openness					-0.0348
					(-1.47)
Adj. R^2	0.072	0.081	0.130	0.149	0.156
Observations	815	815	815	815	815
Standard errors adjusted for clustering	Individual	Individual	Individual	Individual	Individual
Fixed effect (session)	Yes	Yes	Yes	Yes	Yes

Note: The table reports OLS regressions at the task level. Predictors are entered as centred numeric trends. All models include session fixed effects, and inference is based on participant-clustered (cluster-robust) t-statistics reported in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Dependent variable is trading-decision accuracy using the irrelevant-data sample (Conditions 4-6). Column specifications are as in Table 5.3.

Table 5.5: Task Complexity and Information Quantity Predict Self-Rated Mental Effort (Conditions 4–6)

	(1)	(2)	(3)	(4)	(5)
Intercept	6.4000***	6.3484***	6.3485***	5.7014***	2.3654
	(15.17)	(15.79)	(15.77)	(5.51)	(1.42)
Complex	0.1797***		0.1777***	0.1775***	0.1772***
	(4.99)		(4.98)	(4.96)	(4.93)
Info_Quant		0.2235	0.2230	0.1895	0.2210
		(1.42)	(1.41)	(1.19)	(1.39)
Complex × Info_Quant			0.0545	0.0544	0.0535
			(1.25)	(1.24)	(1.22)
Risk Aversion				-0.0952	-0.0107
				(-0.72)	(-0.08)
Gender				0.2533	0.1667
				(0.74)	(0.45)
Fin_edu				-0.0804	-0.0610
				(-0.57)	(-0.45)
Invest_Exp				0.3909	0.4971**
				(1.64)	(2.07)
Fin_literacy				-0.0821	-0.1151
				(-0.58)	(-0.85)
Extraversion					-0.0439
					(-0.28)
Agreeableness					-0.0835
					(-0.42)
Conscientiousness					0.4539**
					(2.34)
Neuroticism					0.3928**
					(2.55)
Openness					-0.0027
					(-0.02)
Adj. R^2	0.034	0.025	0.040	0.051	0.093
Observations	805	805	805	805	805
Standard errors adjusted for clustering	Individual	Individual	Individual	Individual	Individual
Fixed effect (session)	Yes	Yes	Yes	Yes	Yes

Note: The table reports OLS regressions at the task level. Predictors are entered as centred numeric trends. All models include session fixed effects, and inference is based on participant-clustered (cluster-robust) t-statistics reported in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Dependent variable is self-rated mental effort (1–9 scale; higher values indicate greater effort) using the irrelevant-data sample (Conditions 4–6). Column specifications are as in Table 5.3.

Table 5.6: Irrelevant Data, Task Complexity, and Information Quantity: IV Calculation Accuracy (Full Study 2 Sample)

	(1)	(2)	(3)	(4)	(5)
Intercept	0.7007***	0.7307***	0.7307***	0.7221***	0.6377***
	(15.55)	(19.47)	(19.44)	(5.60)	(3.54)
Complex	-0.0689***		-0.0668***	-0.0668***	-0.0668***
	(-8.75)		(-8.94)	(-8.93)	(-8.91)
Info_Quant		-0.1321***	-0.1321***	-0.1306***	-0.1252***
		(-5.55)	(-5.54)	(-5.34)	(-5.04)
Complex × Info_Quant			-0.0424***	-0.0424***	-0.0424***
			(-5.12)	(-5.11)	(-5.11)
Irrelevant	-0.0349	-0.0404	-0.0404	-0.0387	-0.0467
	(-1.07)	(-1.40)	(-1.40)	(-1.33)	(-1.60)
Irrelevant × Complex	0.0099		0.0088	0.0088	0.0088
	(0.89)		(0.83)	(0.83)	(0.83)
Irrelevant × Info_Quant		0.0183	0.0183	0.0170	0.0080
		(0.52)	(0.52)	(0.48)	(0.22)
Irrelevant × Complex × Info_Quant			0.0111	0.0111	0.0111
			(0.93)	(0.93)	(0.93)
Risk Aversion				-0.0060	-0.0008
				(-0.41)	(-0.05)
Gender				-0.0001	0.0021
				(-0.00)	(0.06)
Fin_edu				-0.0133	-0.0065
				(-0.78)	(-0.39)
Invest_Exp				0.0208	0.0225
				(0.70)	(0.79)
Fin_literacy				0.0084	0.0060
				(0.60)	(0.43)
Extraversion					0.0061
					(0.35)
Agreeableness					0.0383*
					(1.78)
Conscientiousness					0.0149
					(0.78)
Neuroticism					-0.0115
					(-0.75)
Openness					-0.0354*
					(-1.67)
Adj. R^2	0.084	0.099	0.174	0.174	0.180
Observations	1645	1645	1645	1645	1645
Standard errors adjusted for clustering	Individual	Individual	Individual	Individual	Individual
Fixed effect	Yes	Yes	Yes	Yes	Yes

Note: Dependent variable is IV calculation accuracy using the full Study 2 sample (Conditions 1–6). Column (1) includes Task Complexity, Irrelevant Data, and Irrelevant × Complex. Column (2) includes Information Quantity, Irrelevant Data, and Irrelevant × Info_Quant. Column (3) includes both trends, Complex × Info_Quant, and the corresponding Irrelevant interactions. Column (4) adds demographic covariates; Column (5) adds the Big Five personality traits. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5.7: Irrelevant Data, Task Complexity, and Information Quantity: Trading-Decision Accuracy (Full Study 2 Sample)

	(1)	(2)	(3)	(4)	(5)
Intercept	0.6013***	0.6390***	0.6390***	0.7168***	0.6565***
	(11.48)	(14.85)	(14.84)	(5.39)	(3.43)
Complex	-0.0770***		-0.0759***	-0.0759***	-0.0759***
	(-10.33)		(-10.27)	(-10.26)	(-10.24)
Info_Quant		-0.1863***	-0.1863***	-0.1829***	-0.1818***
		(-8.76)	(-8.75)	(-8.29)	(-8.16)
Complex × Info_Quant			-0.0221**	-0.0221**	-0.0221**
			(-2.46)	(-2.46)	(-2.45)
Irrelevant	-0.0218	-0.0279	-0.0279	-0.0273	-0.0284
	(-0.68)	(-1.02)	(-1.02)	(-0.99)	(-1.02)
Irrelevant × Complex	0.0212*		0.0207*	0.0207*	0.0207*
	(1.95)		(1.92)	(1.92)	(1.91)
Irrelevant × Info_Quant		0.0595*	0.0595*	0.0558*	0.0566*
		(1.88)	(1.88)	(1.77)	(1.76)
Irrelevant × Complex × Info_Quant			0.0043	0.0043	0.0043
			(0.33)	(0.33)	(0.33)
Risk Aversion				-0.0104	-0.0087
				(-0.80)	(-0.64)
Gender				-0.0153	-0.0111
				(-0.44)	(-0.32)
Fin_edu				-0.0298	-0.0276
				(-1.63)	(-1.51)
Invest_Exp				0.0033	0.0041
				(0.11)	(0.14)
Fin_literacy				0.0127	0.0128
				(0.99)	(0.99)
Extraversion					0.0016
					(0.10)
Agreeableness					-0.0022
					(-0.11)
Conscientiousness					0.0180
					(0.90)
Neuroticism					-0.0038
					(-0.27)
Openness					-0.0044
					(-0.22)
Adj. R^2	0.073	0.129	0.195	0.200	0.198
Observations	1645	1645	1645	1645	1645
Standard errors adjusted for clustering	Individual	Individual	Individual	Individual	Individual
Fixed effect	Yes	Yes	Yes	Yes	Yes

Note: Dependent variable is trading-decision accuracy using the full Study 2 sample (Conditions 1–6). Column specifications are as in Table 5.6. All models include session fixed effects, and inference is based on participant-clustered (cluster-robust) t-statistics reported in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5.8: Irrelevant Data, Task Complexity, and Information Quantity: Self-Rated Mental Effort (Full Study 2 Sample)

	(1)	(2)	(3)	(4)	(5)
Intercept	5.9379***	5.8603***	5.8605***	4.4633***	2.4176**
	(17.17)	(17.40)	(17.38)	(6.42)	(2.06)
Complex	0.1695***		0.1679***	0.1662***	0.1664***
	(4.79)		(4.80)	(4.73)	(4.73)
Info_Quant		0.5681***	0.5679***	0.5444***	0.4228**
		(3.32)	(3.31)	(3.21)	(2.47)
Complex $\times$ Info_Quant			0.0417	0.0414	0.0409
			(1.00)	(0.99)	(0.98)
Irrelevant	0.3135	0.3114	0.3110	0.3498*	0.3272*
	(1.53)	(1.56)	(1.55)	(1.78)	(1.70)
Irrelevant $\times$ Complex	0.0104		0.0101	0.0117	0.0112
	(0.21)		(0.20)	(0.23)	(0.22)
Irrelevant $\times$ Info_Quant		-0.4286*	-0.4282*	-0.4311*	-0.3073
		(-1.76)	(-1.76)	(-1.80)	(-1.28)
Irrelevant $\times$ Complex $\times$ Info_Quant			0.0136	0.0135	0.0134
			(0.23)	(0.22)	(0.22)
Risk Aversion				-0.0603	0.0007
				(-0.68)	(0.01)
Gender				0.4501*	0.3907
				(1.85)	(1.60)
Fin_edu				0.1534	0.1496
				(1.51)	(1.51)
Invest_Exp				0.3166*	0.3757**
				(1.87)	(2.23)
Fin_literacy				-0.0275	-0.0554
				(-0.33)	(-0.66)
Extraversion					-0.1493
					(-1.37)
Agreeableness					-0.0065
					(-0.04)
Conscientiousness					0.2510*
					(1.66)
Neuroticism					0.3027***
					(2.95)
Openness					0.0310
					(0.23)
Adj. R^2	0.050	0.062	0.075	0.093	0.120
Observations	1610	1610	1610	1610	1610
Standard errors adjusted for clustering	Individual	Individual	Individual	Individual	Individual
Fixed effect	Yes	Yes	Yes	Yes	Yes

Note: Dependent variable is self-rated mental effort (1–9 scale; higher values indicate greater effort) using the full Study 2 sample (Conditions 1–6). Column specifications are as in Table 5.6. All models include session fixed effects, and inference is based on participant-clustered (cluster-robust) t-statistics reported in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5.9: Robustness: Irrelevant Data, Task Complexity, and Information Quantity Predict IV Calculation Accuracy (Restricted Sample)

	(1)	(2)	(3)	(4)	(5)
Intercept	0.7694***	0.7902***	0.7902***	0.7249***	0.6675***
	(20.87)	(32.24)	(32.17)	(10.17)	(6.22)
Complex	-0.0691***		-0.0697***	-0.0697***	-0.0697***
	(-8.69)		(-11.23)	(-11.20)	(-11.18)
Info_Quant		-0.1343***	-0.1343***	-0.1307***	-0.1281***
		(-8.37)	(-8.35)	(-8.06)	(-7.50)
Complex × Info_Quant			-0.0564***	-0.0564***	-0.0564***
			(-8.69)	(-8.67)	(-8.64)
Irrelevant	-0.0427	-0.0351*	-0.0351*	-0.0342*	-0.0399**
	(-1.63)	(-1.88)	(-1.88)	(-1.82)	(-2.02)
Irrelevant × Complex	0.0104		0.0128	0.0128	0.0128
	(0.89)		(1.29)	(1.28)	(1.28)
Irrelevant × Info_Quant		0.0036	0.0036	0.0054	0.0024
		(0.16)	(0.16)	(0.24)	(0.10)
Irrelevant × Complex × Info_Quant			0.0117	0.0117	0.0117
			(1.07)	(1.07)	(1.06)
Risk Aversion				0.0102	0.0141
				(1.02)	(1.37)
Gender				-0.0113	-0.0178
				(-0.58)	(-0.91)
Fin_edu				-0.0029	0.0005
				(-0.27)	(0.05)
Invest_Exp				0.0142	0.0152
				(0.90)	(0.96)
Fin_literacy				0.0142	0.0109
				(1.38)	(1.11)
Extraversion					0.0097
					(0.78)
Agreeableness					0.0236
					(1.63)
Conscientiousness					0.0193
					(1.59)
Neuroticism					-0.0049
					(-0.53)
Openness					-0.0340**
					(-2.38)
Adj. R^2	0.153	0.212	0.386	0.390	0.397
Observations	980	980	980	980	980
Standard errors adjusted for clustering	Individual	Individual	Individual	Individual	Individual
Fixed effect	Yes	Yes	Yes	Yes	Yes

Note: Dependent variable is IV calculation accuracy using the restricted sample that excludes any participant who ever recorded 0% IV accuracy at any task-complexity level. Column specifications are as in Table 5.6. All models include session fixed effects, and inference is based on participant-clustered (cluster-robust) t-statistics reported in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5.10: Robustness: Irrelevant Data, Task Complexity, and Information Quantity Predict Trading-Decision Accuracy (Restricted Sample)

	(1)	(2)	(3)	(4)	(5)
Intercept	0.6725***	0.7000***	0.7000***	0.6636***	0.7121***
	(12.68)	(17.94)	(17.90)	(6.36)	(4.37)
Complex	-0.0834***		-0.0839***	-0.0839***	-0.0839***
	(-9.669)		(-11.03)	(-11.00)	(-10.97)
Info_Quant		-0.1882***	-0.1882***	-0.1891***	-0.1830***
		(-9.14)	(-9.12)	(-8.73)	(-8.32)
Complex × Info_Quant			-0.0460***	-0.0460***	-0.0460***
			(-5.30)	(-5.28)	(-5.27)
Irrelevant	-0.0494	-0.0382	-0.0382	-0.0338	-0.0327
	(-1.46)	(-1.50)	(-1.50)	(-1.29)	(-1.19)
Irrelevant × Complex	0.0270**		0.0286**	0.0286**	0.0286**
	(2.05)		(2.32)	(2.31)	(2.31)
Irrelevant × Info_Quant		0.0359	0.0359	0.0375	0.0340
		(1.22)	(1.22)	(1.26)	(1.13)
Irrelevant × Complex × Info_Quant			0.0189	0.0189	0.0189
			(1.29)	(1.29)	(1.28)
Risk Aversion				0.0085	0.0099
				(0.64)	(0.71)
Gender				0.0103	0.0104
				(0.41)	(0.40)
Fin_edu				-0.0158	-0.0139
				(-0.80)	(-0.69)
Invest_Exp				0.0280	0.0305
				(1.21)	(1.34)
Fin_literacy				0.0011	0.0020
				(0.08)	(0.15)
Extraversion					0.0093
					(0.57)
Agreeableness					-0.0119
					(-0.56)
Conscientiousness					0.0197
					(1.10)
Neuroticism					-0.0101
					(-0.76)
Openness					-0.0213
					(-1.17)
Adj. R^2	0.105	0.197	0.301	0.301	0.301
Observations	980	980	980	980	980
Standard errors adjusted for clustering	Individual	Individual	Individual	Individual	Individual
Fixed effect	Yes	Yes	Yes	Yes	Yes

Note: Dependent variable is trading-decision accuracy using the restricted sample that excludes any participant who ever recorded 0% IV accuracy at any task-complexity level. Column specifications are as in Table 5.6. All models include session fixed effects, and inference is based on participant-clustered (cluster-robust) t-statistics reported in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5.11: Robustness: Irrelevant Data, Task Complexity, and Information Quantity Predict Self-Rated Mental Effort (Restricted Sample)

	(1)	(2)	(3)	(4)	(5)
Intercept	5.8172***	5.7569***	5.7569***	5.3133***	2.6127*
	(16.15)	(16.58)	(16.55)	(5.87)	(1.79)
Complex	0.2432***		0.2428***	0.2429***	0.2428***
	(5.37)		(5.34)	(5.32)	(5.31)
Info_Quant		0.4288**	0.4266**	0.4290**	0.3309
		(2.01)	(2.00)	(2.01)	(1.53)
Complex × Info_Quant			0.0465	0.0465	0.0462
			(0.84)	(0.83)	(0.82)
Irrelevant	0.1422	0.1110	0.1115	0.1170	0.0974
	(0.54)	(0.44)	(0.44)	(0.48)	(0.40)
Irrelevant × Complex	0.0160		0.0130	0.0130	0.0129
	(0.26)		(0.21)	(0.21)	(0.21)
Irrelevant × Info_Quant		-0.0756	-0.0746	-0.1085	0.0120
		(-0.24)	(-0.24)	(-0.36)	(0.04)
Irrelevant × Complex × Info_Quant			0.0341	0.0342	0.0343
			(0.47)	(0.47)	(0.47)
Risk Aversion				-0.1616	-0.1353
				(-1.45)	(-1.17)
Gender				-0.0482	-0.0767
				(-0.13)	(-0.21)
Fin_edu				0.2578**	0.2534**
				(2.12)	(2.19)
Invest_Exp				0.1548	0.1443
				(0.68)	(0.63)
Fin_literacy				0.0040	-0.0078
				(0.04)	(-0.07)
Extraversion					-0.0959
					(-0.67)
Agreeableness					0.1078
					(0.55)
Conscientiousness					0.2178
					(1.17)
Neuroticism					0.2471**
					(2.02)
Openness					0.1384
					(0.78)
Adj. R^2	0.095	0.090	0.121	0.135	0.158
Observations	971	971	971	971	971
Standard errors adjusted for clustering	Individual	Individual	Individual	Individual	Individual
Fixed effect	Yes	Yes	Yes	Yes	Yes

Note: Dependent variable is self-rated mental effort (1–9 scale; higher values indicate greater effort) using the restricted sample that excludes any participant who ever recorded 0% IV accuracy at any task-complexity level. Column specifications are as in Table 5.6. All models include session fixed effects, and inference is based on participant-clustered (cluster-robust) t-statistics reported in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5.12: Robustness check: Original and entropy-balanced estimates for Study 2

	IV accuracy		Trading accuracy		Mental effort	
	Original	Entropy	Original	Entropy	Original	Entropy
Complex	-0.0668***	-0.0713***	-0.0759***	-0.0784***	0.1664***	0.1768***
	(-8.91)	(-7.73)	(-10.24)	(-8.16)	(4.73)	(3.86)
Info_Quant	-0.1252***	-0.1213***	-0.1818***	-0.1934***	0.4228**	0.5056**
	(-5.04)	(-3.85)	(-8.16)	(-7.84)	(2.47)	(2.38)
Irrelevant	-0.0467	-0.0305	-0.0284	0.0217	0.3272*	0.5132**
	(-1.60)	(-0.81)	(-1.02)	(0.65)	(1.70)	(2.00)
Complex × Irrelevant	0.0088	0.0249*	0.0207*	0.0264**	0.0112	-0.0363
	(0.83)	(1.87)	(1.91)	(1.97)	(0.22)	(-0.54)
Info_Quant × Irrelevant	0.0080	-0.0525	0.0566*	0.0263	-0.3073	-0.3428
	(0.22)	(-1.11)	(1.76)	(0.73)	(-1.28)	(-1.09)
Complex × Info_Quant	-0.0424***	-0.0478***	-0.0221**	-0.0174	0.0409	0.0222
	(-5.11)	(-4.87)	(-2.45)	(-1.61)	(0.98)	(0.44)
Complex × Info_Quant × Irrelevant	0.0111	0.0096	0.0043	-0.0158	0.0134	0.0723
	(0.93)	(0.68)	(0.33)	(-1.05)	(0.22)	(0.91)
Risk Aversion	-0.0008	-0.0153	-0.0087	-0.0199	0.0007	0.1717
	(-0.05)	(-0.91)	(-0.64)	(-1.31)	(0.01)	(1.43)
Gender	0.0021	0.0057	-0.0111	0.0043	0.3907	0.2590
	(0.06)	(0.14)	(-0.32)	(0.12)	(1.60)	(0.93)
Fin_edu	-0.0065	0.0330*	-0.0276	0.0124	0.1496	0.1288
	(-0.39)	(1.67)	(-1.51)	(0.65)	(1.51)	(0.93)
Invest_Exp	0.0225	0.0487*	0.0041	0.0329	0.3757**	0.4414**
	(0.79)	(1.72)	(0.14)	(1.24)	(2.23)	(2.39)
Fin_literacy	0.0060	-0.0080	0.0128	0.0120	-0.0554	0.0797
	(0.43)	(-0.49)	(0.99)	(0.67)	(-0.66)	(0.81)
Extraversion	0.0061	0.0069	0.0016	0.0137	-0.1493	-0.1138
	(0.35)	(0.31)	(0.10)	(0.77)	(-1.37)	(-0.83)
Agreeableness	0.0383*	0.0054	-0.0022	-0.0259	-0.0065	0.0200
	(1.78)	(0.20)	(-0.11)	(-1.18)	(-0.04)	(0.10)
Conscientiousness	0.0149	0.0152	0.0180	0.0169	0.2510*	0.1479
	(0.78)	(0.58)	(0.90)	(0.71)	(1.66)	(0.77)
Neuroticism	-0.0115	0.0062	-0.0038	0.0080	0.3027***	0.2832**
	(-0.75)	(0.33)	(-0.27)	(0.46)	(2.95)	(2.12)
Openness	-0.0354*	-0.0370	-0.0044	-0.0118	0.0310	0.0876
	(-1.67)	(-1.36)	(-0.22)	(-0.47)	(0.23)	(0.46)
Adj. R^2	0.180	0.214	0.198	0.239	0.120	0.135
Observations	1645	1625	1645	1625	1610	1590
Standard errors adjusted for clustering	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effect (session)	Yes	Yes	Yes	Yes	Yes	Yes
Participant controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports OLS regressions at the task level for Study 2. The original specifications use the full student analysis sample. Entropy-balanced specifications include participants identifying as male or female. Female participants are reweighted to match male participants on financial education, investment experience, and financial literacy. The entropy weights are constructed at the participant level and the same weight is applied to all five repeated observations. The original participant controls and session fixed effects are retained, with standard errors clustered at the participant level. Clustered t-statistics appear in parentheses. Zero-coded missing mental-effort responses are excluded. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Chapter 6

The impact of time constraint on mental effort and decision quality

6.1 Study 3 motivation and design

Study 3 examines whether the core relationships documented in Study 1 are sensitive to the amount of time participants have to process information and complete the task. Psychological accounts of time pressure often emphasise a speed-accuracy trade-off. When the available time is tight, decision makers may curtail information search, simplify trade-offs, and rely more heavily on salient cues or rules of thumb. This type of early stopping is consistent with cognitive-closure arguments and should be most consequential when decisions require integrating multiple inputs. In the present setting, the valuation and trading tasks are designed to become progressively more demanding as task complexity rises and as the amount of information increases, so time pressure may be expected to matter most in the high-demand region. This motivates hypotheses 4a and 4b. Higher time pressure should reduce decision quality, and it may also increase perceived mental effort.

The experimental structure mirrors Study 1's information-quantity and task-complexity design, while varying the time constraint. Participants are randomly assigned to one of two timing regimes. Conditions 1-3 impose a 3-minute limit per question, while Conditions 7-9 allow 5 minutes. Work on decisional styles and tracked online behaviour suggests that time pressure can induce "hypervigilant, inefficient search patterns" (Mann & Tan, 1993), where greater activity does not necessarily translate into higher-quality outcomes (Phillips & Landhuis, 2022). Within each timing regime, information quantity varies across three levels, and task complexity varies across five levels. Complexity provides within-participant variation across tasks, whereas information quantity and time constraint vary between participants across conditions. The outcomes are intrinsic-value calculation accuracy, trading-decision accuracy, and self-rated mental effort.

The Study 3 student sample combines the observations from the 166 participants in Study 1, who completed Conditions 1–3 under the 3-minute time limit, with 168 newly recruited participants who completed Conditions 7–9 under the 5-minute time limit. Conditions 7–9 correspond to Conditions 1–3 in information quantity and task structure, with the time available per question increased from three to five minutes. Importantly, each participant took part in only one experimental condition. The 166 Study 1 participants were not re-tested for Study 3. Instead, their original observations form the 3-minute comparison group, while Conditions 7–9 were completed by a separate group of newly recruited participants. The comparison between the two time windows is therefore a between-participants comparison and is not subject to a learning or familiarity effect arising from repeated participation.

Because each participant completes multiple tasks, the analysis is conducted at the task level. The main models follow the Study 1 approach, using centred numeric trends for task complexity and information quantity, session fixed effects, and standard errors clustered by participant. The descriptive section that follows first checks balance and correlation patterns across timing regimes, then summarises raw performance and effort patterns by matched condition pairs, before turning to regression estimates that isolate time effects and test whether time pressure moderates the complexity and information-quantity relationships.

6.2 Descriptive analysis

6.2.1 Balance and correlations

Study 3 examines whether loosening the time constraint changes performance and perceived workload, comparing matched condition pairs that hold information quantity and task materials constant. Participants completed the same information-quantity and task-complexity structure as in Study 1, but under two timing regimes: Conditions 1-3 imposed a 3-minute limit per question (higher time pressure), whereas Conditions 7-9 imposed a 5-minute limit (lower time pressure). The combined sample comprises $N = 334$ students, with $N = 166$ in the 3-minute group and $N = 168$ in the 5-minute group. Table 6.1 reports descriptive statistics for key demographics and Big Five traits by time-constraint group, together with tests of mean and median differences.

In terms of observed characteristics, the two timing groups appear broadly comparable. To assess balance, I test for differences between the 3-minute and 5-minute groups using two-sided tests of equality, reporting mean-comparison p-values. Most variables show very small differences in central tendency, with insignificant tests (e.g., risk aversion: 3-minute Mean (M) = 2.33, Standard Deviation (SD) = 1.06 vs. 5-minute $M = 2.35$, $SD = 1.07$, $\Delta M = -0.02, p = 0.864$; financial literacy: 3-minute $M = 4.01$, $SD = 1.10$ vs. 5-minute $M = 4.05$, $SD = 1.02$, $\Delta M = -0.04$, $p = 0.720$). The same close-to-neutral pattern holds for age, gender, and financial education (all $p \geq 0.10$), as well as for Extraversion, Agreeableness, Conscientiousness, and Neuroticism (all $p \geq .287$). Two variables, however, show small but detectable differences. Investment experience is slightly higher in the 3-minute group (3-minute $M = 1.37$, $SD = 0.58$; 5-minute $M = 1.21$, $SD = 0.47$; $\Delta M = 0.15$, $p = 0.008$; small effect, Cohen's $d \approx 0.299$)[9], and Openness is also modestly higher under the 3-minute constraint (3-minute $M = 4.35$, $SD = 0.77$; 5-minute $M = 4.18$, $SD = 0.72$; $\Delta M = 0.17, p = 0.040$; $d \approx 0.23$). Median-based tests indicate a similar direction for Openness (median difference = 0.25, $p = 0.007$), suggesting a slight distributional shift rather than a difference driven by a small number of extreme observations. In essence, these imbalances appear minor, but they provide a sensible rationale for retaining the standard

[9]Cohen's d is not reported directly in Table 6.1; it is computed post hoc from the table's group means and standard deviations using the pooled standard deviation and is used here only as a standardised measure of the magnitude of the between-group difference.

set of controls in the main models so that the estimated time-constraint effect is not inadvertently picking up background differences in experience or trait openness.

6.2.2 Descriptive outcome patterns

Table 6.2 presents bivariate correlations among the independent variables and covariates (pooled $N = 334$). The correlation structures show several Big Five traits cluster moderately (e.g., Agreeableness-Conscientiousness $r = 0.451$, Agreeableness-Openness $r = 0.377$, Conscientiousness-Openness $r = 0.370$, and Extraversion-Openness $r = 0.3$), while most other associations are small. Among the demographic and financial background measures, Age shows a modest positive correlation with investment experience, and females have moderately higher risk aversion and lower investment experience than males. Importantly, the largest absolute correlation in the matrix is 0.451, which does not raise serious concerns about multicollinearity (Tabachnick & Fidell, 2007). Taken together, these descriptives suggest that the two time-constraint groups are reasonably comparable and that the covariate set is suitable for regression adjustment, with no obvious correlation patterns that would undermine the interpretability of the main effects and interactions tested in Study 3.

Figure 6.1 compares Condition 1 (low information load, 3 minutes per question; $N = 52$) and Condition 7 (low information load, 5 minutes per question; $N = 60$) across five levels of task complexity for both intrinsic-value calculation accuracy and trading-decision accuracy. In this low information quantity setting, performance is already relatively high under the tighter 3-minute constraint, so the benefit of extending the time window to 5 minutes is present but not uniform across complexity levels. For IV calculation accuracy, Condition 1 begins at 86.54% at complexity level 1, then sits at around 75.00% from levels 2 to 4, before ending at 72.12% at level 5. Under the more relaxed timing in Condition 7, IV accuracy is 83.33% at level 1, remains in the low-to-mid 80s thereafter, peaking at 87.50% at level 3, and finishes at 81.67% at level 5. Averaged across complexity levels, IV accuracy is about 7.44 percentage points higher with 5 minutes, although the easiest level is an exception where Condition 7 is slightly lower.

A similar pattern appears for trading decisions. Under the 3-minute regime, trading accuracy declines from 88.46% at level 1 to 69.23% at level 5, whereas under the 5-minute regime, it remains higher at the upper end of the range, finishing at 85.00% at level 5. On average, trading accuracy is about 4.82 percentage points higher in Condition 7, and the largest difference occurs at the highest complexity level, where the gap is 15.77 percentage points. For the condition-pair differences in proportions, I summarise standardised gaps using Cohen's h. Cohen's h is about 0.09 for IV at complexity level 1 and about 0.23 at level 5, while the trading gap at level 5 corresponds to $h \approx 0.38$, which is small to moderate by conventional benchmarks. This is consistent with the idea that when information load is low, the time constraint is less likely to bind except at the most demanding tasks.

Figure 6.2 shows that under a medium information load, the timing contrast is materially larger than in the low-load panel. This is broadly in line with prior information-overload accounts, which suggest that as the information set becomes richer, decision makers require more time to screen cues and integrate them into a coherent judgement. Under tight deadlines, accuracy tends to suffer most when processing demands are high, and the risk of overload increases when time pressure coincides with heavier information load environments (Iselin, 1988; Hahn et al., 1992; Payne et al., 1996).

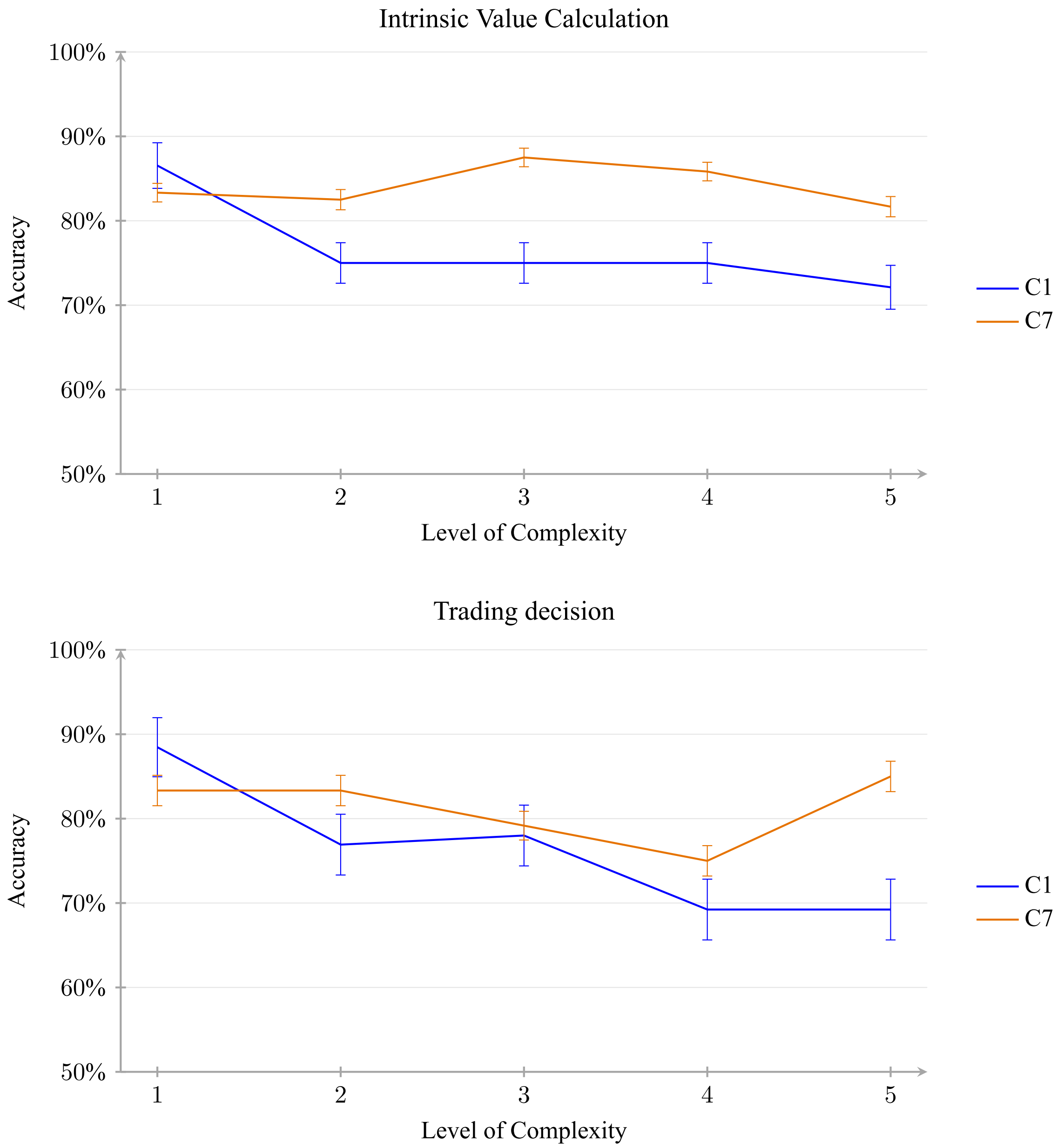

Figure 6.1: Intrinsic value calculation and trading decision accuracy (%) in Condition 1 versus Condition 7

In the 3-minute condition, IV calculation accuracy declines from 68.06% at task complexity level 1 to 40.74% at level 5, indicating a steep deterioration as complexity rises. Under the 5-minute condition, IV accuracy is higher at every complexity level, starting at 96.76% and remaining at 81.02% at level 5. Averaged across complexity levels, the improvement associated with easing the time constraint is about 31.94 percentage points, and it increases with task difficulty. At level 5 the gap is 40.28 percentage points. Trading accuracy exhibits the same qualitative pattern. Under the 3-minute regime it falls from 68.52% at level 1 to 31.48% at level 5, whereas under the 5-minute regime it declines more gradually from 92.59% to 67.59%. These differences are also large in standardised terms. Using Cohen's h for differences in proportions, the IV gap corresponds to $h \approx 0.84$ at complexity level 1 and $h \approx 0.86$ at level 5, while the trading gap corresponds to $h \approx 0.64$ at level 1 and $h \approx 0.74$ at level 5, which places the medium-load timing effect in the medium-to-large range by conventional benchmarks. The mean improvement is about 27.78 percentage points, with larger gaps at higher levels of complexity. In general, once participants face a moderate amount of information, the 3-minute limit appears more likely to bind. Providing an extra two minutes is associated with a substantial recovery in accuracy, particularly on the more complex items where cue integration and checking should be most time intensive.

The high-information-load patterns in Figure 6.3 point in the same direction, but the time-by-complexity contrast is more pronounced. Under the 3-minute constraint, performance deteriorates more sharply as tasks become more challenging. In Condition 3, IV calculation accuracy falls from 71.94% at complexity level 1 to 23.61% at level 5. In Condition 9, the decline is materially smaller, with accuracy decreasing from 83.02% to 54.63% across the same range. Averaged across complexity levels, the relaxed time constraint is associated with an improvement of about 21.59 percentage points, and this difference increases monotonically with complexity, from 11.08 percentage points at level 1 to 31.02 percentage points at level 5. Trading decisions show a similarly consistent separation. Condition 3 declines from 59.17% at level 1 to 21.67% at level 5, whereas Condition 9 declines from 78.40% to 51.85%, implying an average difference of roughly 25.72 percentage points, rising to 30.19 percentage points at level 5. Using Cohen's h for differences in proportions, the IV gap at level 5 corresponds to $h \approx 0.65$ and the trading gap to $h \approx 0.64$, which exceeds Cohen's 0.50 benchmark for a medium effect. Overall, these high-information-load comparisons suggest that time pressure does more than reduce performance levels. It also steepens the difficulty gradient, with the largest losses emerging precisely where cognitive demands should be highest, namely at high complexity within a high information load environment.

Across all three information-load panels, a consistent pattern emerges. Extending the time window from 3 to 5 minutes per question is associated with higher IV calculation accuracy and higher trading accuracy, and the difference is most pronounced at higher task complexity. This suggests that time pressure affects performance mainly when cognitive demands are greatest. These figures are useful for documenting the raw gaps in accuracy between the 3-minute and 5-minute conditions across complexity levels. However, they do not establish whether the gaps are attributable to time pressure alone or partly reflect compositional differences between groups, such as the slightly higher investment experience and Openness in the 3-minute sample. The regression analysis therefore serves two purposes. It conditions on participant characteristics to isolate the timing effect more cleanly, and it estimates the average effect of time alongside interactions with task complexity and information load within a single framework.

Figure 6.4 presents the descriptive pattern for self-rated mental effort across task complexity levels under the two time-constraint regimes used in Study 3. Each panel compares conditions that are matched

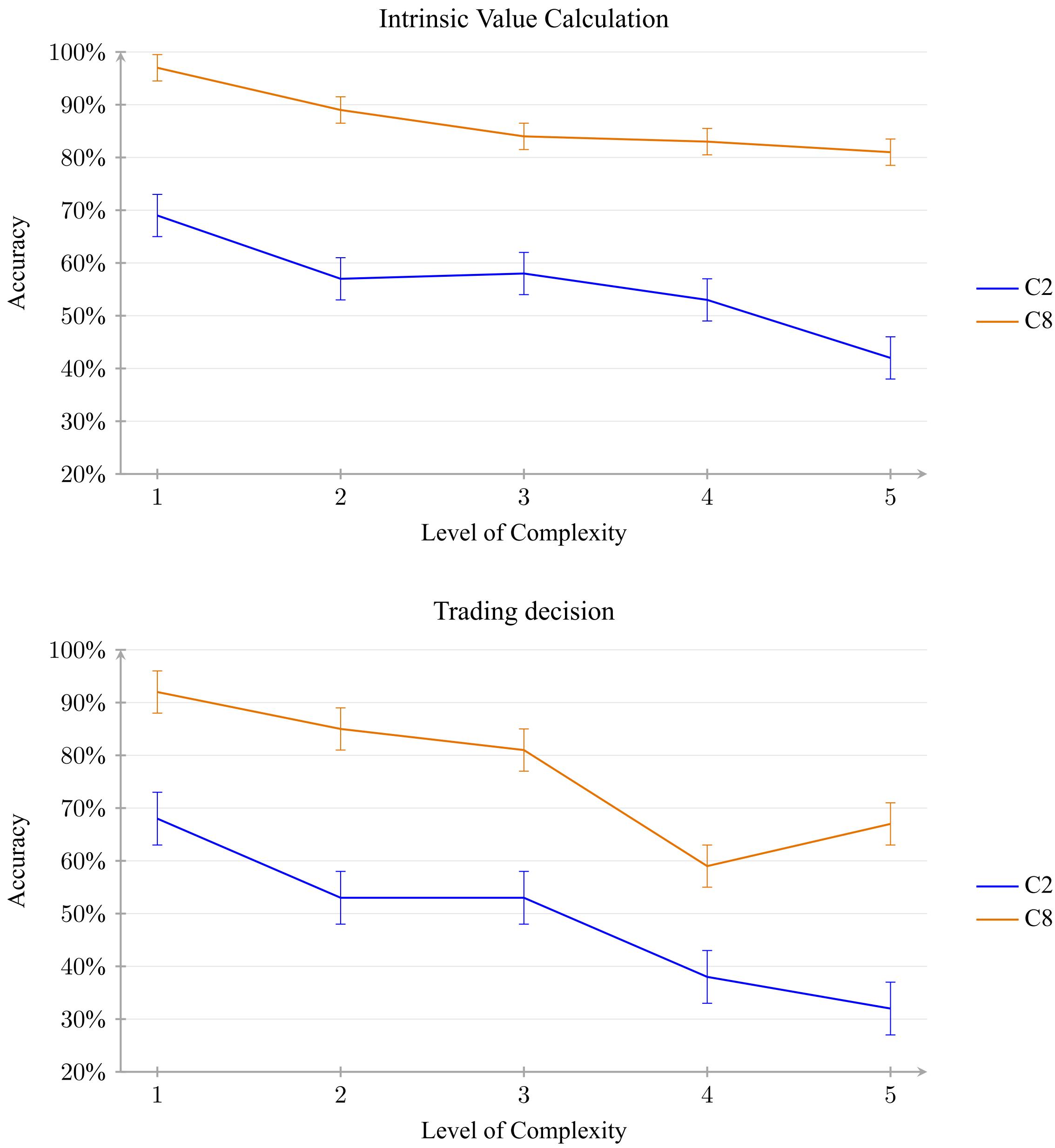

Figure 6.2: Intrinsic value calculation and trading decision accuracy (%) in Condition 2 versus Condition 8

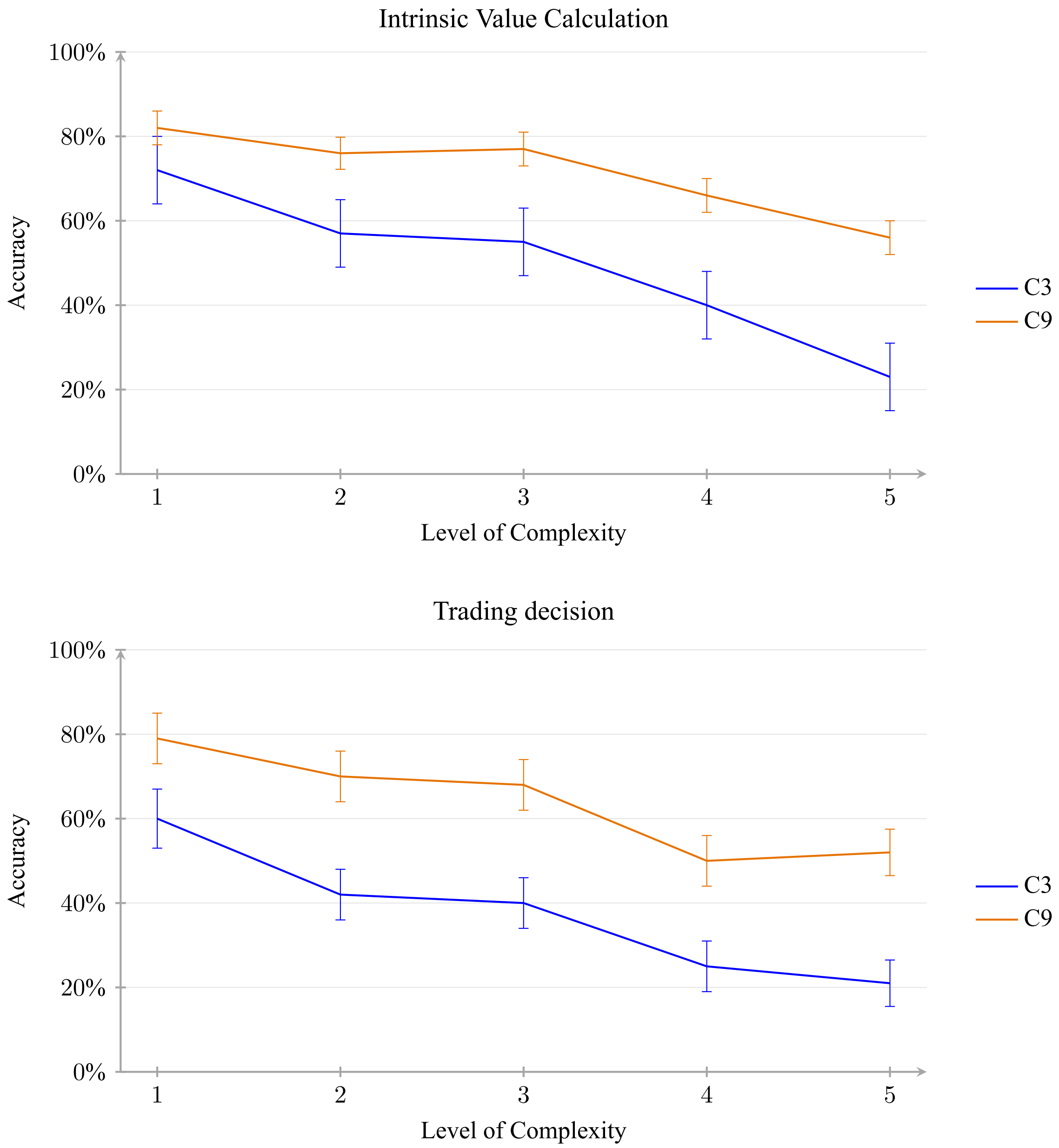

Figure 6.3: Intrinsic value calculation and trading decision accuracy (%) in Condition 3 versus Condition 9

on information quantity and task structure, differing only in the time allowed per question. Conditions 1-3 impose a 3-minute limit (higher time pressure), while Conditions 7-9 impose a 5-minute limit (lower time pressure). Specifically, panel (a) contrasts C1 vs. C7 (low information load), panel (b) contrasts C2 vs. C8 (medium information load), and panel (c) contrasts C3 vs. C9 (high information load). Mental effort is plotted across the five complexity levels, allowing for a visual check of whether relaxing the time constraint reduces the perceived workload overall and whether any time-pressure effect becomes more pronounced as cognitive demands increase.

In the low information load comparison between Conditions 1 and 7, self-rated mental effort remains within a narrow range under both timing regimes, and the two series track each other closely across the five complexity levels. Under the tighter 3-minute limit in Condition 1, effort increases modestly from 5.19 at complexity level 1 to 5.77 at level 5 ($M = 5.52$). Under the 5-minute limit in Condition 7, effort is very similar, rising from 5.20 to 5.70 ($M = 5.47$). The average difference is therefore about 0.05 points on the 1-9 scale, which is small in practical terms. In this low-load setting, easing the time constraint does not appear to change the perceived demand of the task, which is consistent with participants having sufficient capacity to process the available information without the time limit becoming a binding constraint.

The medium information-load panel comparing Conditions 2 and 8 shows a more pronounced timing contrast. Under the 3-minute limit in Condition 2, mental effort rises from 5.60 at complexity level 1 to a peak of 6.40 at level 4, before easing slightly to 5.91 at level 5 ($M = 5.92$). Under the 5-minute limit in Condition 8, effort follows a smoother and consistently lower trajectory, increasing from 5.09 to 5.81 across the complexity range ($M = 5.58$). Averaged across levels, the tighter-time condition is therefore about 0.34 points higher in perceived effort, and the separation is most evident toward the more demanding end of the series. For example, at complexity level 4, the gap is roughly 0.64 points. This pattern implies that timing becomes more consequential once the information set goes beyond a bare minimum. As integration demands rise, the tighter time limit appears to translate into higher reported mental effort.

The high information-load comparison between C3 and C9 is where the timing manipulation seems to matter most for self-rated mental effort. In Condition 3, effort begins high at 6.07 and rises to 7.10 by task complexity level 4, before easing slightly to 6.95 at level 5 ($M = 6.72$). In Condition 9, perceived effort is lower at every complexity level and increases more gradually, from 5.50 to 6.63 ($M = 6.09$). The average gap is about 0.63 points in favour of the longer time window, and it is most pronounced in the mid-to-high complexity range, for example, at level 3, where the difference is roughly 0.95 points. This pattern is consistent with the idea that, under high information load, tighter timing acts as an additional processing constraint. Participants not only show weaker performance in the accuracy figures, but they also report that the task feels heavier when the available time is limited.

Taken together, the three panels suggest a coherent demand-sensitive effect of time pressure on subjective workload. Mental effort rises as information load increases (average effort under 3-minute conditions moves from about 5.52 in low load to 5.92 in medium and 6.72 in high), and the benefit of relaxing the time limit becomes progressively larger (roughly 0.05, 0.34, and 0.63 points for low, medium, and high information load, respectively). So, the timing manipulation does not appear to matter much when the information environment is simple, but it becomes increasingly consequential as the tasks get

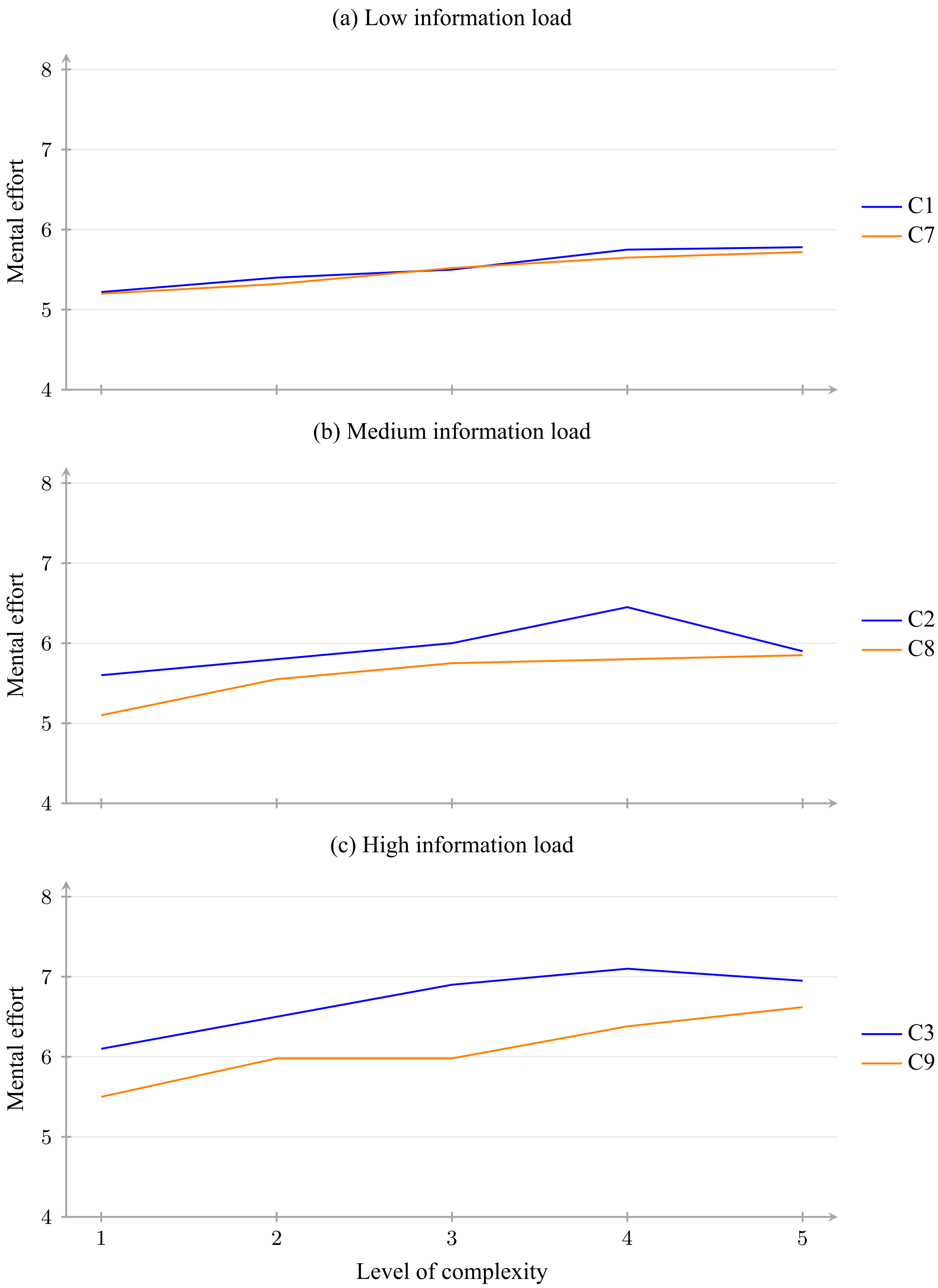

Figure 6.4: Comparisons of the mean self-rated mental effort as a function of time pressure and task complexity

cognitively heavier, which is exactly the setting where a tighter clock is most likely to be experienced as genuine time pressure rather than just a procedural rule. The fact that the timing gap widens as complexity rises, and becomes largest under medium and high information load, is consistent with a processing-time account. When tasks require integrating more cues and performing more steps, the 3-minute limit is more likely to bind, pushing participants toward earlier closure or simplified rules.

6.3 Regression Model

The effect of time constraint on decision quality and self-rated mental effort is examined by running the following regression model:

$$\begin{aligned} Y_{pi} = \alpha_1 &+ \beta_1\, \textit{Complex}_{pi} + \beta_2\, \textit{Info\_Quant}_p + \beta_3\, \textit{Time}_p \\ &+ \beta_4(\textit{Complex}_{pi} \times \textit{Time}_p) + \beta_5(\textit{Info\_Quant}_p \times \textit{Time}_p) \\ &+ \beta_6(\textit{Complex}_{pi} \times \textit{Info\_Quant}_p) + \beta_7(\textit{Complex}_{pi} \times \textit{Info\_Quant}_p \times \textit{Time}_p) \\ &+ \gamma X_p + \varepsilon_{pi} \end{aligned} \tag{6.1}$$

where Y_{pi} denotes decision quality (the percentage correct in intrinsic value calculations and trading decisions) or self-rated mental effort for participant p at task-complexity level i. Task complexity is coded as a centred numeric trend, *Complex* $\in \{-2, -1, 0, 1, 2\}$ for levels 1-5 (0 corresponds to level 3), and information quantity is coded as *Info_Quant* $\in \{-1, 0, 1\}$ for levels 1-3 (0 corresponds to level 2). Time is a dummy variable equal to 1 when the time limit is 5 minutes per question and 0 when it is 3 minutes per question. X_p is a vector of between-subject controls[10] (gender, financial education, experience, financial literacy, risk tolerance, and the Big Five traits), and standard errors are clustered by participant to account for repeated observations across complexity levels.

With centred coding, β_1 captures the complexity slope at the reference time condition (*Time* $= 0$) and at the midpoint of information quantity (*Info_Quant* $= 0$). β_2 captures the information-quantity slope at the midpoint of complexity (*Complex* $= 0$) and *Time* $= 0$. β_3 captures the average shift in the outcome when moving from the tighter to the more relaxed time limit (from 3 to 5 minutes), evaluated at the midpoints of complexity and information quantity. The interaction terms capture whether the marginal effects of complexity and information quantity change when the time constraint is relaxed. In particular, the coefficient on *Complex* $\times$ *Time* shows how the complexity slope differs under 5 minutes relative to 3 minutes. Under the 3-minute regime (*Time* $= 0$), the marginal effect of complexity equals β_1. Under the 5-minute regime (*Time* $= 1$), it equals $\beta_1 + \beta_4$. A positive β_4 therefore implies that additional time attenuates the negative complexity gradient, whereas a negative β_4 implies that the complexity gradient becomes steeper when more time is available. The coefficient on *Info_Quant* $\times$ *Time* is interpreted analogously. Under the 3-minute condition, the marginal effect of information quantity equals β_2, and under 5 minutes it equals $\beta_2+\beta_5$. A positive β_5 indicates that the information-quantity penalty is weaker when participants have more time. β_6 captures whether the complexity slope changes as information quantity increases (the two-way interaction), and β_7 tests whether this *Complex* $\times$ *Info_Quant* interaction itself differs across time conditions (the three-way interaction).

[10]Since all participants are in the same age group, Age is not included in the control variables set.

6.4 Regression results

6.4.1 Robustness of Study 1 results

Using the 5-minute time-constraint subsample (Conditions 7-9; $N = 168$), the robustness regressions largely reproduce the core Study 1 pattern. Decision quality declines as tasks become more complex and as information quantity increases, while perceived mental effort rises. The two design factors also appear to combine in a non-additive way. Even with more time available, the estimates continue to indicate a compounding relationship in which the marginal effect of complexity depends on the information environment, and the marginal effect of information quantity depends on task complexity. The models are estimated at the task level (840 observations for IV and trading, 835 for mental effort), include session fixed effects, and use standard errors clustered at the participant level. The main inferences are unchanged when the full set of controls is added, including the Big Five personality traits.

In Table 6.3, IV calculation accuracy remains negatively related to both task complexity and information quantity, and the interaction between the two is strongly negative. In column (5), which includes the full set of controls, a one-step increase in complexity is associated with a roughly 3.39 percentage point reduction in IV accuracy, and a one-step increase in information quantity with a 6.21 percentage point reduction, holding the other terms constant. In terms of economic significance, with mean IV accuracy in Conditions 7-9 of about 81%, these shifts are equivalent to declines of roughly 4.19% and 7.67% relative to that baseline level, and they appear smaller in magnitude than the corresponding effects reported in Studies 1 and 2. The interaction term is -0.0329 and statistically significant at the 1% level, which implies that the marginal penalty from complexity becomes more severe as information quantity rises, and likewise the penalty from additional information becomes larger as tasks become more complex. The implied marginal effect of complexity at a given information quantity level follows directly from the interaction specification. It equals the complexity coefficient plus the interaction coefficient multiplied by the coded information level. Because information quantity is entered as a centred numeric trend, low, medium, and high information load correspond to -1, 0, and $+1$. Under low information load, the marginal effect of complexity is $-0.0339 + (-0.0329 \times -1) = -0.0010$, or about -0.10 percentage points per complexity step, which is roughly -0.40 percentage points across the full four-step complexity range. At medium information, the marginal effect is $-0.0339 + (-0.0329 \times 0) = -0.0339$, or about -3.39 percentage points per step, which is roughly -13.57 percentage points across the range. At high information, the marginal effect is $-0.0339 + (-0.0329 \times 1) = -0.0668$, or about -6.68 percentage points per step, which is roughly -26.74 percentage points across the range. This preserves the same qualitative shape as in Conditions 1-3, with complexity most damaging when information load is high, which is consistent with a cognitive-load account in which dense information environments amplify the costs of rising task demands.

Trading decision accuracy in Table 6.4 provides a particularly clear replication of the non-additive, compounding pattern. In column (5), which includes the full set of controls, the complexity trend is -0.0508 and the information-quantity trend is -0.0848. These coefficients imply declines of 5.08 percentage points and 8.48 percentage points for each one-step increase in complexity and information quantity, respectively, holding the other terms constant. In terms of economic significance, these represent decreases of 6.87% and 11.45% in trading decision accuracy (given the mean value in Conditions 7-9 is

74%). Similar to IV accuracy, these figures appear smaller in magnitude than the corresponding effects reported in Studies 1 and 2. The interaction term is -0.0345 and is statistically significant at the 1% level, indicating that the marginal cost of complexity increases as information quantity increases, and that the marginal cost of additional information increases as tasks become more complex. The implied marginal effect of complexity at a given information level follows directly from the interaction specification. It equals the complexity coefficient plus the interaction coefficient multiplied by the coded information level, where information quantity is entered as a centred numeric trend and therefore takes values of -1, 0, and $+1$ for low, medium, and high information, respectively. Under low information, the marginal effect of complexity is $-0.0508 + (-0.0345 \times -1) = -0.0163$, which corresponds to about -1.63 percentage points per complexity step, or roughly -6.52 percentage points across the full four-step complexity range. The implied complexity slope is modest under low information load, but it steepens at medium information load (about -5.08 percentage points per step, and approximately -20.33 percentage points across the range) and becomes largest at high information load (about -8.54 percentage points per step, and approximately -34.15 percentage points across the range). This pattern aligns with the Study 1 conclusion that trading judgements are most vulnerable when the decision environment is simultaneously information-heavy and cognitively demanding. Adding covariates leaves the focal coefficients largely unchanged. In the fully controlled model, a small positive association appears for financial literacy at about $+3.39$ percentage points and for Openness at about $+4.02$ percentage points, while the core complexity-information quantity pattern remains intact.

For self-rated mental effort, Table 6.5 shows the expected sign reversal relative to the accuracy outcomes. Reported effort increases with both task complexity and information quantity, and the interaction term is positive, indicating that the effort cost of complexity is higher when more information is provided. In column (5), which includes the full set of controls, the complexity trend is 0.1885 and the information-quantity trend is 0.3314. These coefficients correspond to increases of about 0.19 points and 0.33 points on the 1-9 effort scale for each one-step increase in complexity and information quantity, respectively, holding the other terms constant. The interaction term is 0.0655 and statistically significant at the 10% level, so the marginal effect of complexity depends on the coded information level. The implied complexity slope rises from roughly 0.12 points per step under low information load (approximately 0.49 across the full complexity range) to 0.19 at medium information load (approximately 0.75 across the full complexity range) and 0.25 at high information load (approximately 1.02 across the full complexity range). This is closely aligned with Study 1. When both task demands and information quantity increase, participants not only perform worse but also feel the tasks become more effortful, consistent with a cognitive-load interpretation. A couple of control coefficients stand out in the effort model (e.g., Openness is negatively associated with effort by about 0.57 points, and financial education is positively associated by approximately 0.34 points), but again, these are secondary to the stable main effects and interaction.

Taken together, the 5-minute subsample results support the view that the Study 1 mechanism is not an artefact of the original timing regime. Under more relaxed time constraints, greater information quantity still amplifies the adverse effect of task complexity on decision quality and is also associated with higher perceived workload as tasks become more demanding. The smaller IV magnitudes relative to Conditions 1-3 do not alter the main inference. In fact, the persistence of the interaction across timing regimes reinforces the idea that participants face a joint burden of limited processing capacity and reduced diagnosticity when information is abundant and tasks are complex. These pressures seem particularly salient for trading judgements, where accuracy gradients remain steep in the high-information load, high-complexity region.

6.4.2 Study 3 results: Effect of time constraint

To assess whether the core Study 1 relationships change when participants are given more time, I re-estimate the task-level models on the pooled sample spanning both the 3-minute and 5-minute regimes, reported in Tables 6.6 to 6.8. The dependent variables are IV calculation accuracy in Table 6.6, trading decision accuracy in Table 6.7, and self-rated mental effort in Table 6.8. Across outcomes, the specifications move from parsimonious models that include time and a single focal driver in columns (1) and (2), to a full specification in columns (3) to (5) that includes task complexity, information quantity, their interaction, time, and the corresponding time-moderation terms. Controls are added in columns (4) and (5). The accuracy models use 1,670 task observations, while the mental-effort model uses 1,640 observations due to some missing effort ratings.

Because complexity and information quantity are centred, the Time coefficient reflects the average timing shift at the midpoints of both dimensions. If timing mainly matters in harder tasks, the interaction terms can be informative even when the main time effect at the midpoints is modest.

IV calculation accuracy

At a descriptive level, the IV regressions continue to indicate that decision quality declines as the task becomes more demanding and as the information set expands. Consistent with Study 1, under the tighter 3-minute regime, the fully controlled specification in column (5) of Table 6.6 shows that a one-step increase in task complexity is associated with a 6.68 percentage-point reduction in IV accuracy, and a one-step increase in information quantity is associated with an additional 11.74 percentage-point reduction, holding other terms constant. The interaction between task complexity and information quantity is also negative in the controlled model, implying that the accuracy cost of complexity becomes steeper as information quantity increases, and that the penalty from additional information becomes larger as tasks become more complex. These focal coefficients are statistically significant at the 1% level.

The time-constraint results are less clear-cut. The main effect of *Time* (5 minutes vs. 3 minutes) is positive in the more parsimonious specifications in columns (1) to (3), but it is not statistically significant once the full set of covariates is included. In contrast, the moderation pattern is stable. The *Time* $\times$ *Complex* term is positive and statistically significant at the 1% level in every specification where it appears, including the fully controlled model in column (5), where $\beta = 0.0329$. This implies that moving from 3 to 5 minutes reduces the accuracy penalty associated with rising complexity. This pattern suggests that extra time in IV calculations is used mainly to manage multi-step computation and checking as complexity rises, rather than to offset the marginal burden of additional information items. Using the column (5) coefficients, the implied marginal effect of complexity at mean information is -6.68 percentage points per step under the 3-minute regime, compared with -3.39 percentage points per step under the 5-minute regime, which corresponds to a reduction of 3.29 percentage points per complexity step. In practical terms, the additional time allowance appears most beneficial in higher-demand tasks, even though the average time main effect at the centred reference point is not robust once covariates are included. By contrast, the *Time* × *Info_Quant* term is small and statistically insignificant in the fully controlled model, and the three-way interaction *Time* × *Complex* × *Info_Quant* is also not significant. Taken together, the IV results suggest that relaxing time constraints primarily dampens the complexity gradient rather than materially altering the underlying complexity-by-information quantity compounding pattern.

Trading decision accuracy

The trading-accuracy results in Table 6.7 tell a similar story for the core Study 1 drivers, but the time-constraint moderation is clearer, especially for information quantity. In column (5), both main effects remain negative and statistically significant at the 1% level. Similar to results from Study 1, a one-step increase in task complexity is associated with a 7.59 percentage-point decrease in trading accuracy, and a one-step increase in information quantity with a 17.72 percentage-point decrease, holding other terms constant. The Complex × Info_Quant interaction is also negative and statistically significant once controls are included, consistent with the compounding difficulty that occurs when both dimensions increase.

More importantly, Table 6.7 helps explain how the timing manipulation shifts the marginal costs of information and complexity. As in the IV models, the *Time* main effect is positive in the parsimonious specifications but becomes statistically insignificant once the full set of controls is added, which suggests that the average difference at the centred reference point is not the most informative summary of timing. The stronger evidence sits in the interaction terms. The *Time* × *Info_Quant* coefficient is positive and highly significant across columns (2) to (5), indicating that the adverse effect of higher information quantity is weaker when participants have more time. Using column (5) as an anchor, the implied marginal effect of information quantity at mean complexity is -17.72 percentage points per step under the 3-minute regime, compared with -8.82 percentage points per step under the 5-minute regime. This corresponds to a reduction in the information-quantity penalty of 8.90 percentage points per step, and it is statistically significant at the 1% level. One reason the timing moderation is stronger for information quantity in trading is that the decision requires mapping a noisy valuation signal into a discrete action. Under time pressure, participants may rely on a smaller subset of salient cues, so an expanded information set adds noise more than value unless there is enough time to screen and integrate it. The *Time* × *Complex* coefficient is also positive and statistically significant at the 5% level, implying a smaller attenuation of the complexity gradient. At the medium level of information quantity, the implied marginal effect of complexity shifts from -7.59 percentage points per step under 3 minutes to -5.08 percentage points per step under 5 minutes, a reduction of 2.51 percentage points per step. The three-way interaction is not statistically significant. Taken together, the trading results indicate that additional time primarily reduces the marginal harm of information quantity, and to a lesser extent complexity, while leaving the underlying complexity-by-information quantity interaction broadly similar in shape beyond these two-way moderation effects.

Self-rated mental effort

For mental effort, Table 6.8 shows that the core relationships remain strong, but the time-constraint manipulation does not translate into detectable changes in reported workload. In the fully controlled model, task complexity is associated with higher effort ratings, and information quantity also increases perceived effort. In contrast to the accuracy outcomes in Tables 6.5 and 6.6, the Complex × Info_Quant interaction is not statistically significant, suggesting that participants' subjective workload rises with both design factors but does not exhibit the same compounding pattern observed in performance once controls are included.

Crucially, for Study 3, *Time* has essentially no detectable relationship with mental effort across all specifications. The *Time* main effect is near zero in column (5), and the time-moderation terms (*Time* × *Complex*, *Time* × *Info_Quant*, and the three-way term) are all statistically insignificant. Although the raw means in Figure 6.4 suggest that time pressure is associated with higher reported effort, especially at higher information loads, this pattern becomes much smaller once the regressions account for complexity, information quantity, their interaction, and the full set of controls, indicating that the apparent gap is largely explained by covariate-adjusted differences rather than a robust direct effect of timing on effort. A possible explanation is that giving participants more time does not make the task feel easier, even though it helps protect performance, particularly by reducing the information quantity penalty in trading decisions. This pattern aligns with a cognitive-load interpretation, in which extra time relaxes processing constraints and enables more careful integration of information, but does not necessarily reduce the intrinsic effort participants experience while working through complex, information-heavy valuation problems. Related evidence suggests that reduced breadth or depth of processing can show up in behavioural markers of engagement, even when it is not mirrored by a clear change in subjective workload, which is consistent with this interpretation (Phillips et al., 2016). Participants can experience the task as demanding in both regimes, and the main behavioural adjustment under tight timing may be strategy simplification, which lowers accuracy without producing a proportional change in self-reported workload.

In summary, across the three outcomes, the evidence suggests that time constraints primarily act as performance moderators rather than direct determinants of perceived effort. Moving from 3 minutes to 5 minutes per question does not produce a robust average improvement at the centred reference point once controls are included, but it does systematically dampen the marginal damage from complexity (IV and trading) and, most strikingly, from information quantity in trading decisions. In practical terms, the trading models indicate that relaxed time roughly halves the per-step information load penalty (from about -17.72 percentage points to -8.82 percentage points at mean task complexity), while the IV models indicate that relaxed time substantially flattens the complexity gradient (from about -6.68 percentage points to -3.39 percentage points at mean information quantity). Meanwhile, mental effort remains driven by task complexity and the quantity of information, with no reliable shift attributable to the additional time allowance.

6.5 Results discussion

In general, the pooled time-constraint results are broadly consistent with Hypothesis 4a, although the evidence points to a moderate rather than uniform time-pressure effect. Under the tighter 3-minute regime, both IV and trading accuracy decline sharply as complexity and information quantity rise, and the negative Complex × Info_Quant term indicates that these penalties compound when the task environment is simultaneously demanding on both dimensions. When participants are given more time, the main Time indicator is not robust in the fully controlled models, but the interaction terms show that timing matters most where processing demands are highest. For IV accuracy, the positive Time $\times$ Complex estimate implies that moving from 3 to 5 minutes substantially flattens the complexity gradient at mean information quantity, from -6.68 to -3.39 percentage points per complexity step. For trading accuracy, moderation is particularly pronounced for information quantity, with the marginal information penalty at mean complexity falling from -17.72 to -8.82 percentage points per step under the 5-minute regime, alongside a smaller attenuation of the complexity gradient. This demand-sensitive pattern fits the theoretical account of time pressure as a constraint on depth of processing. When time is scarce, participants appear more likely to truncate search and integration, consistent with cognitive closure and a shift toward simpler decision rules (Kruglanski & Freund, 1983) that can generate systematic errors (Tversky & Kahneman, 1974) or preference reversals in multi-attribute settings (Diederich, 1997). In that sense, Study 3 supports Hypothesis 4a most strongly in the high-demand region, where additional time relaxes the binding constraint and enables more complete processing of complex, information-heavy valuation problems.

I then turn to whether the same timing pattern is reflected in perceived workload, as Hypothesis 4b predicts. The evidence for Hypothesis 4b is weaker once task demands and covariates are taken into account. Descriptively, tighter timing is associated with higher reported effort, particularly under high information load, but Table 6.8 indicates that the time indicator and its moderation terms are statistically insignificant in the fully controlled specification. Instead, mental effort continues to be driven primarily by task complexity and information quantity, with no clear incremental shift attributable to the time allowance. This combination is informative for the mechanism. It suggests that time pressure may reduce accuracy partly through a strategy shift toward earlier closure or more selective cue use, rather than through a sustained increase in experienced workload. Participants can meet the deadline by simplifying processing, which can lower decision quality without necessarily raising self-rated effort in a stable way once objective demands are held constant. Overall, Study 3 supports Hypothesis 4a, while providing only limited support for Hypothesis 4b, and reinforces the broader interpretation that time pressure primarily changes the effectiveness of processing under high cognitive demand rather than directly increasing perceived effort.

6.6 Robustness check

6.6.1 Exclusion of non-performance

To assess sensitivity to extreme non-performance, I re-estimate the pooled time-constraint models after excluding any participant who recorded 0% IV accuracy at any task-complexity level, yielding a restricted sample of $N = 236$. This restriction is informative because repeated floor performance is unlikely to reflect time pressure alone. It may instead capture misunderstanding of the valuation task, disengagement, or a response strategy that effectively collapses the task into guessing. In those cases, extending the time window from 3 minutes to 5 minutes would not be expected to generate systematic gains, since the binding constraint is not processing time. Removing such observations therefore sharpens inference about the role of time pressure among participants who appear to engage with the task and for whom limited time can plausibly truncate information processing. The specifications in Tables 6.9-

6.11 mirror the earlier regression. Columns (1)-(2) estimate the bivariate time-moderation patterns for complexity and information quantity separately, while columns (3)-(5) include the full set of main effects and interaction terms, with controls added in columns (4)-(5) (column (5) includes Big Five). All regressions are estimated at the task level, using individual-clustered standard errors and session fixed effects, yielding 1,180 observations for IV and trading accuracy and 1,170 for mental effort.

For IV calculation accuracy, Table 6.9 preserves the core Study 1 structure and makes the timing effects more pronounced. In the fully controlled specification, IV accuracy declines with complexity at -6.97 percentage points per step and with information quantity at -13.35 percentage points per step, and the *Complex* $\times$ *Info_Quant* interaction remains strongly negative at -5.64 percentage points, consistent with compounding difficulty when tasks are both complex and information-heavy. Relative to the full-sample estimates, the Time indicator is now clearly positive and statistically significant at $+10.70$ percentage points. The interaction terms also become more informative. *Time* $\times$ *Complex* is positive at $+3.52$ percentage points, implying that the complexity gradient at mean information quantity is substantially flatter under 5 minutes, shifting from -6.97 to -3.45 percentage points per step. *Time* $\times$ *Info_Quant* is positive at $+6.37$ percentage points, indicating that additional time also weakens the information penalty. Importantly, the three-way interaction is positive and statistically significant at $+2.33$ percentage points, which implies that extra time reduces part of the compounding itself. Under 3 minutes, the compounding effect is -5.64 percentage points. Under 5 minutes, it becomes $-5.64 + 2.33 = -3.30$ percentage points, so the interaction remains negative but is less steep. This pattern fits the mechanism behind Hypothesis 4a. When time is tight, participants may reach cognitive closure earlier and rely more on simplified processing, which increases errors in settings that require integrating multiple cues, consistent with the closing-of-the-mind account and heuristics-based judgment under constraint. Once repeated floor performers are removed, the timing manipulation more cleanly reveals benefits that are concentrated where the task is most demanding, particularly when complexity and information quantity jointly rise.

For trading decision accuracy, Table 6.10 is very similar to the earlier full-sample results, which reinforces the view that time primarily moderates marginal processing costs rather than generating a uniform level shift. In the fully controlled model, trading accuracy declines with complexity at -8.39 percentage points per step and with information quantity at -18.53 percentage points per step, and the Complex $\times$ Info_Quant interaction is negative at -4.60 percentage points. The *Time* main effect is positive but only weakly significant at $+10.51$ percentage points, while *Time* $\times$ *Complex* and *Time* $\times$ *Info_Quant* are positive and statistically significant at $+2.95$ and $+8.20$ percentage points, respectively. These estimates imply that extending the time limit reduces the implied complexity penalty from -8.39 to -5.44 percentage points per step at mean information quantity, and reduces the implied information penalty from -18.53 to -10.33 percentage points per step at mean complexity. The three-way interaction remains statistically insignificant, suggesting that extra time primarily dampens the separate marginal harms of complexity and information quantity in trading, rather than altering the shape of their joint interaction. A natural intuition is that trading decisions add an additional step beyond valuation, namely mapping the valuation signal into a buy or sell choice. Extra time plausibly helps with careful screening and integration of a larger information set, which is where the moderation is strongest, but the compounding difficulty created by simultaneously high complexity and high information quantity still remains. The emergence of a significant three-way term for IV in the restricted sample is consistent with time slack reducing the joint difficulty of combining high complexity with high information. For trading, the mechanism appears closer to a reduction in separate marginal penalties, consistent with extra time helping cue screening and action mapping without materially changing the underlying interaction shape.

For self-rated mental effort, Table 6.11 again indicates that the time constraint does not reliably shift perceived workload once task demands are controlled. In the fully controlled specification, effort increases with complexity at about $+0.24$ points per step on the 1 to 9 scale and is positively related to information quantity at about $+0.42$ points per step, while the *Complex* $\times$ *Info_Quant* interaction is not statistically significant. The Time main effect is near zero, and the time-moderation terms are statistically insignificant, mirroring the full-sample findings. This divergence between accuracy and effort is also interpretable. If time pressure induces a strategy shift toward earlier closure or cue simplification, performance can fall without a parallel increase in perceived effort, because simplifying the decision process may keep experienced workload relatively stable even as accuracy deteriorates. In that sense, the restricted-sample results strengthen support for Hypothesis 4a, while leaving limited support for Hypothesis 4b in the regression-adjusted models.

Overall, excluding repeated 0% IV performers clarifies that the timing manipulation operates most clearly among engaged participants and primarily in high-demand environments. The restricted-sample results sharpen the evidence that relaxing time pressure improves decision quality, and for IV accuracy, it also weakens part of the compounding effect, which is consistent with time pressure constraining depth of processing and encouraging earlier closure in complex, information-rich tasks.

I also repeat the entropy-balancing robustness analysis for Study 3. Female participants are reweighted to match male participants on financial education, investment experience, and financial literacy, with the original session fixed effects, participant controls, and participant-clustered standard errors retained. Table 6.15 shows that the main effects of task complexity and information quantity remain stable, and the key moderating effects of additional time continue to hold. Some secondary coefficients change in statistical significance after weighting, but the substantive conclusion that additional time mitigates performance losses under demanding conditions remains unchanged.

6.7 External validity with sample of professional finance participants

To assess the external validity of the student-based findings, I conduct a targeted replication with 60 finance professionals. The professional experiment focuses on the high-information-load setting used in Study 3. Participants are randomly and evenly assigned to either Condition 3 or Condition 9. In both conditions, each question contains six companies and participants complete tasks across the same five levels of task complexity used in the student experiment. The informational content and task structure are therefore held constant across the two professional conditions. The only experimental difference is the time available per question. Condition 3 imposes a 3-minute time limit, while Condition 9 allows 5 minutes. Accordingly, the professional analysis examines whether relaxing the time constraint affects decision quality and mental effort under high information load, and whether the resulting patterns are comparable with those observed among students in the corresponding conditions.

6.7.1 Replication experiment with financial professionals

To assess external validity, I repeat the Study 3 experiment with financial professionals. I recruited 60 professionals from financial institutions in Vietnam, including securities brokers and investment analysts. All financial professionals who took part in the experiment routinely faced investment and trading decisions in their day-to-day work. 63.33% were male, and the majority are above 25 years old and have more than 2 years of experience. Consistent with prior work (Cohn et al., 2014; Alevy et al., 2007; List et al., 2005; Cao et al., 2022), professionals' payoffs were scaled to three times the student stakes across all parts of the experiment, amounting to 300,000 VND. This amount is considered substantial enough to incentivise these professional participants, given their average daily income of around 1,000,000 VND.

Given their substantial investment experience, finance professionals were asked to complete only the two highest information-load conditions, Conditions 3 and 9. In total, 60 professionals were randomly and evenly assigned to these two conditions. The informational environment is held constant across them. Participants are shown the same high number of companies and the same set of information items in both conditions, so information quantity does not vary within the professional sample. The key difference is the time constraint. Condition 3 imposes a 3-minute limit per question, whereas Condition 9 allows 5 minutes. Within each condition, participants still complete tasks across the full five-level task-complexity structure, so complexity varies at the task level in the same way as in the student experiments. Accordingly, the professional regressions focus on the effect of time and its interaction with task complexity. Information quantity is not included as a regressor because it is fixed by design and provides no identifying variation in this sample.

Table 6.12 indicates that, under high information load, allowing professionals 5 minutes rather than 3 minutes to respond is associated with substantially higher accuracy in both IV calculations and trading decisions. The estimated differences are around 20-28 percentage points, depending on the outcome and the specification. Task complexity continues to impose a large accuracy penalty, which suggests that additional time improves overall performance but does not eliminate the fundamental difficulty posed by more demanding tasks. In contrast, professionals' self-rated mental effort increases with complexity and shows little systematic change when the time window is extended. The evidence for *Time* $\times$ *Complex* moderation is also limited. The 5-minute regime appears to shift performance upward across complexity levels, rather than materially flattening the complexity gradient. For professionals, the extra time appears to raise accuracy across the board, which is consistent with using time slack for verification and error checking at all complexity levels, rather than changing sensitivity to complexity per se. I discuss each dependent variable in turn below.

a) Intrinsic value calculation accuracy (IV) IV accuracy declines sharply as task complexity increases. In the baseline specification without controls in column (1), each one-step increase in task complexity is associated with an estimated 11.94 percentage-point reduction in IV accuracy, and this gradient remains very similar once demographic covariates and personality traits are added in columns (4) and (5). By contrast, the time constraint is associated with a sizeable upward shift in performance. In column (1), moving from 3 minutes to 5 minutes corresponds to an increase of about 22.78 percentage points in IV accuracy, and this estimate is statistically significant at the 5% level. The coefficient remains comparable when demographic controls are added in column (4), and becomes larger in the full specification in column (5), where it is significant at the 1% level. The stability of the time coefficient across specifications is consistent with the idea that the timing difference is not driven by observable covariate imbalance.

However, there is little indication that extra time changes how strongly complexity hurts IV accuracy. The *Time* $\times$ *Complex* coefficient is small and statistically insignificant, implying that the complexity slope under 5 minutes is only slightly less negative than under 3 minutes.

b) Trading decision accuracy (DA) The accuracy of trading decisions also deteriorates as complexity increases. In the baseline specification in column (2), each one-step increase in complexity is associated with an estimated 9.67 percentage-point reduction in trading accuracy, and this gradient remains essentially unchanged once covariates are added in columns (6) and (7). The time-constraint effect points in the expected direction, with higher trading accuracy under the 5-minute regime, although the evidence becomes clearer in the controlled specifications. In column (2), the *Time* coefficient is positive but not statistically significant. With demographic controls added in column (6), the estimated difference increases to about 20.35 percentage points and is marginally significant, and in the full specification in column (7) it rises to about 24.55 percentage points and is statistically significant at the 5% level. Given random assignment and the relatively small professional sample, the strengthening of the time coefficient after adding controls is most plausibly attributed to sampling variation rather than a substantive suppression mechanism. Even so, the central inference is stable. Allowing more time is associated with higher trading accuracy, and the estimate remains of similar order once covariates are included.

As with intrinsic value accuracy, there is no clear evidence that extra time systematically moderates the complexity penalty on trading decision accuracy. The *Time* $\times$ *Complex* coefficient is small and insignificant, implying broadly similar complexity gradients under 3 and 5 minutes.

c) Self-rated mental effort (ME) Professionals report higher mental effort as task complexity increases. In the baseline specification in column (3), each one-step increase in complexity is associated with an increase of about 0.231 points on the 1-9 mental-effort scale, and this relationship remains similar once demographic covariates and personality traits are added in columns (8) and (9). In contrast to the accuracy outcomes, perceived effort does not vary systematically with the time allowance. The 5-minute main effect is negative across specifications but is not statistically significant, for example, in column (9) where β is about -0.312. The *Time* $\times$ *Complex* term is also negative, which is consistent with a slightly flatter effort gradient under the longer time window, but it is not statistically significant.

6.7.2 Comparison to the student time-constraint results

Relative to the student sample (which spans multiple information-load conditions), the professional results under high information load show a different shape of the time effect. In the student sample, additional time mainly worked through interaction effects, flattening the complexity gradient and, in some cases, dampening the compounding impact of task demands. In the professional high-load setting, by contrast, the dominant pattern is a main-effect improvement in accuracy (around 20-28 percentage points), with only weak evidence that time moderates the complexity slope (*Time* $\times$ *Complex*). One plausible interpretation is that when expertise and task familiarity are higher, extra time is primarily used for verification and error-checking (raising overall correctness) rather than fundamentally altering sensitivity to complexity. At the same time, the ME results echo the student pattern. Extra time improves performance more than it reduces experienced workload, consistent with a cognitive-load account in which time slack supports additional checking without necessarily changing the subjective effort of processing dense, complex information.

6.7.3 External validity of the student sample in a professional finance con- text

To examine whether the student-based effects extend to a more experienced decision-making population, I compare performance and self-rated effort between the student sample and a professional sample drawn from Vietnamese financial institutions, specifically securities brokers and investment analysts. Because professionals completed only the high information-load task, the external validity analysis focuses on the two matched high-information conditions, Condition 3 and Condition 9, which hold the task-complexity and information-quantity structure constant but differ in the time constraint. Condition 3 imposes a 3-minute limit per question, whereas Condition 9 allows 5 minutes. Within each condition, I estimate pooled task-level regressions of the form in equation 6.2 below,

$$Y_{pi} = \alpha_1 + \beta_1\, Complex_{pi} + \beta_2\, Pro_p + \beta_3(Complex_{pi} \times Pro_p) + \gamma X_p + \varepsilon_{pi} \tag{6.2}$$

where Y_{pi} denotes decision quality (the percentage correct in intrinsic value calculations and trading decisions) or self-rated mental effort for participant p at task-complexity level i. Task complexity is coded as a centred numeric trend, $Complex \in \{-2, -1, 0, 1, 2\}$ for levels 1-5 (0 corresponds to level 3), and Pro is a dummy variable equal to 1 for finance professionals and 0 for students. $Complex_{pi} \times Pro_p$ allows the complexity gradient to differ between professionals and students. X_p is a vector of between-subject controls (gender, financial education, experience, financial literacy, risk tolerance, and the Big Five traits), and standard errors are clustered by participant to account for repeated observations across complexity levels. Specifications add covariates sequentially, beginning with no controls, then only demographic controls, and finally the full set including personality traits. The main conclusions are similar across specifications, so the discussion emphasises the fully adjusted models.

In Table 6.13, where the time limit for each question is 3 minutes, the pooled models show a strong and consistent complexity penalty that is largely shared across students and professionals. In the full IV model, complexity is associated with an estimated 11.94 percentage point decrease in IV accuracy per complexity step. The professional main effect is small and statistically insignificant, and the Complex $\times$ Pro interaction is also negligible, suggesting near-parallel complexity gradients for professionals and students in this time-pressure setting. An analogous pattern holds for trading decision accuracy, as complexity reduces it by about 9.67 percentage points per step, with neither the professional level difference nor the slope difference being significant. For mental effort, task complexity increases perceived effort, while professional status does not systematically shift either average effort or the complexity-effort slope.

Taken together, the 3-minute condition suggests that under high time pressure, expertise offers limited scope to offset complexity-related performance losses. Professional and student responses are similar in both statistical and substantive terms. This supports the external validity of the student-based estimates for high information load decision settings in which decisions must be made under tight timing constraints.

In Condition 9, with a 5-minute time limit per question, the pooled specifications in Table 6.14 again show a strong complexity penalty for students, and the professional-student gap becomes more pronounced. In the full IV model, complexity is associated with an estimated decline of 11.61 percentage points per step for students. Professional investors show a sizeable conditional advantage at the mid level of task complexity, and, critically, a statistically significant attenuation of the complexity penalty, with *Pro* $\times$ *Complex* significant at the 5% level. Substantively, this interaction indicates that the complexity gradient is markedly flatter for professionals than for students. This suggests that, under relaxed time constraints, professionals' IV computation is less sensitive to increases in task complexity. The flatter professional complexity gradient under the relaxed regime is consistent with expertise being partly latent under tight deadlines. When time is available, professionals can deploy more diagnostic routines, such as cross-checking cues and revisiting intermediate calculations, which are difficult to execute under severe time pressure.

For trading decision accuracy, complexity remains strongly negative for students, and professionals again show higher conditional accuracy. However, the evidence that expertise alters the complexity gradient of trading decision accuracy is weaker, as the interaction term *Pro* $\times$ *Complex* is positive but not statistically significant, suggesting that the professional advantage in trading decisions under low time pressure operates primarily as an overall level shift rather than a distinct complexity slope. For mental effort, complexity increases effort, but neither the professional main effect nor the interaction provides consistent evidence of expertise-driven differences in subjective workload.

Across the professional-student comparison regressions, the covariate pattern suggests that investment experience matters for accuracy mainly when the task environment affords enough time to apply that experience, whereas neuroticism shows up more clearly in experienced workload than in performance. Under the tighter constraint, investment experience is small and statistically insignificant for both IV and trading accuracy once covariates are included, consistent with a setting where even knowledgeable participants have limited scope to translate background experience into higher-quality integration. Under the more relaxed constraint, by contrast, investment experience becomes a reliable positive correlate of decision quality. In the controlled specifications it is associated with roughly 7.65 to 8.71 percentage points higher IV accuracy and 7.93 to 9.38 percentage points higher trading accuracy. In the same Condition 9 regressions, neuroticism is positively associated with self-rated mental effort in the full specification, while remaining weakly related to accuracy outcomes, suggesting that personality differences are expressed more strongly in subjective workload than in objective performance once task structure is controlled. This neuroticism-mental effort association lines up with prior evidence that personality shapes the experience of workload and stress even when objective task demands are held constant. In applied and laboratory settings, higher neuroticism (lower emotional stability) is often linked to greater perceived workload, frustration, and stress responses during demanding tasks, and to stronger coupling between task demands and subjective strain (Szalma & Taylor, 2011; Chiorri et al., 2015). A common interpretation is that neuroticism is associated with greater threat sensitivity and intrusive worry, which can consume working-memory resources and make the same task feel more effortful, effectively adding an "emotional load" component on top of cognitive load. That framing matches the present result well, as neurotic participants may not necessarily perform worse once covariates are accounted for, but they report higher mental effort, consistent with the idea that personality differences show up more clearly in experienced workload than in accuracy when task structure and incentives are fixed.

6.7.4 Results discussion: External validity of the student sample in a professional finance context

In general, these results support a bounded claim about external validity. The professional sample reproduces the qualitative structure that is central to the study's mechanism. Greater task complexity systematically reduces accuracy and increases self-rated mental effort, and this pattern holds in the pooled student-professional comparisons under both time regimes. The magnitudes are not identical across populations, but the direction and shape of the relationships remain stable. This aligns with the view that external validity is often most credibly assessed through qualitative replication of core effects, rather than by expecting near-identical effect sizes across samples and decision environments (Kessler & Vesterlund, 2015).

At the same time, the professional comparison pinpoints a sensible boundary condition. Expertise becomes more visible when time pressure is relaxed. Under the 3-minute condition, professional and student responses are statistically very similar, which is consistent with the "properties of the situation" arguments that emphasise how constraints such as deadlines can compress behavioural differences by limiting the strategies decision makers can feasibly deploy (Harrison & List, 2004; Levitt & List, 2007). Under a more relaxed time condition, professionals exhibit higher conditional accuracy and, for IV calculation, a clearly flatter complexity gradient, suggesting that time slack allows experienced participants to engage in more diagnostic checking and error correction, as adaptive strategy accounts would predict (Payne et al., 1993; Maule et al., 2000). This also aligns with experimental finance evidence that professionals can behave differently from students in controlled market tasks, for example, through better signal-quality discrimination and greater price efficiency, even when the broad behavioural patterns overlap (Alevy et al., 2007; Weitzel et al., 2020).

Empirically, work in behavioural and experimental finance suggests that investment experience can improve decision quality through both learning and bias attenuation. Retail investors appear to learn from trading experience, with prior forecasting success predicting later trade profitability and activity, and some investors becoming better traders over time (Nicolosi et al., 2009; Seru et al., 2010). Experience and sophistication have also been linked to weaker behavioural biases, including a reduced disposition effect and lower overconfidence (Feng & Seasholes, 2005; Dhar & Zhu, 2006; Gloede & Menkhoff, 2014). In controlled financial tasks, professionals are also better able than students to discriminate the quality of public signals, suggesting stronger mappings between cues and outcomes (Alevy et al., 2007). In the present context, that logic is especially plausible because the valuation and trading tasks reward structured integration of multiple inputs. When participants have more time, experienced individuals may be better able to deploy deliberative checking, cross-cue consistency tests, and error correction. This interpretation is also consistent with evidence that tighter deadlines reduce information search and shift choice processes toward simpler, less diagnostic rules, with less-experienced decision makers often more adversely affected by time pressure (Payne, 1976; Ahituv et al., 1998; Maule et al., 2000). In combination, the pattern in this chapter, where experience predicts accuracy under Condition 9 but not under tighter timing, is consistent with the idea that expertise can be partly latent under severe time pressure and becomes behaviourally expressed once the task affords sufficient time for it to be deployed.

Table 6.1: Descriptive Statistics and Balance Tests: Conditions 1–3 vs Conditions 7–9

	Condition 123 ($N = 166$)					Condition 789 ($N = 168$)					Test of Difference in			
Variable	Mean	Median	Stdev	Min	Max	Mean	Median	Stdev	Min	Max	Mean	p-value	Median	p-value
Risk Aversion	2.325	2.000	1.057	1.000	4.000	2.345	2.000	1.067	1.000	4.000	−0.020	0.864	0.000	0.871
Age	1.006	1.000	0.078	1.000	2.000	1.036	1.000	0.393	1.000	6.000	−0.030	0.338	0.000	0.567
Gender	1.753	2.000	0.498	1.000	4.000	1.845	2.000	0.525	1.000	4.000	−0.092	0.100	0.000	0.125
Financial Education	2.747	3.000	0.879	1.000	6.000	2.732	3.000	0.705	1.000	6.000	0.015	0.865	0.000	0.637
Investment experience	1.367	1.000	0.575	1.000	4.000	1.214	1.000	0.466	1.000	4.000	0.153	0.008***	0.000	0.006***
Financial Literacy	4.006	4.000	1.098	0.000	5.000	4.048	4.000	1.020	1.000	5.000	−0.042	0.720	0.000	0.843
Extraversion	3.670	3.750	0.898	1.000	6.000	3.658	3.750	0.779	1.250	5.750	0.012	0.893	0.000	0.995
Agreeableness	4.554	4.750	0.817	1.000	6.000	4.646	4.750	0.751	2.500	6.000	−0.092	0.287	0.000	0.455
Conscientiousness	4.212	4.250	0.770	2.250	6.000	4.188	4.250	0.676	2.250	5.750	0.025	0.754	0.000	0.618
Neuroticism	4.175	4.250	1.012	1.250	6.000	4.141	4.250	0.959	1.500	6.000	0.033	0.758	0.000	0.777
Openness	4.349	4.500	0.766	1.000	6.000	4.182	4.250	0.721	2.000	6.000	0.168	0.040**	0.250	0.007***

Note: This table summarises participant characteristics for the 3-minute time-constraint group (Conditions 1–3) and the 5-minute time-constraint group (Conditions 7–9). It reports the mean, median, standard deviation, and range for each covariate by group, alongside tests of differences in means and medians between the two samples. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6.2: Correlation matrix ($N = 334$).

	1	2	3	4	5	6	7	8	9	10	11
1 Risk Aversion	1										
2 Age	0.036	1									
3 Gender	-0.257^{**}	0.111^{*}	1								
4 Financial Education	-0.124^{*}	0.211^{**}	0.129^{*}	1							
5 Investment experience	0.201^{**}	0.280^{**}	-0.261^{**}	-0.063	1						
6 Financial Literacy	0.070	0.028	-0.090	0.033	0.104	1					
7 Extraversion	0.044	-0.068	-0.018	-0.131^{*}	0.035	0.044	1				
8 Agreeableness	-0.115^{*}	-0.009	0.031	-0.095	-0.078	0.031	0.271^{**}	1			
9 Conscientiousness	-0.133^{*}	0.020	-0.009	-0.173^{**}	0.023	-0.023	0.101	0.451^{**}	1		
10 Neuroticism	-0.183^{**}	-0.028	0.148^{**}	0.051	-0.125^{*}	-0.048	-0.042	0.216^{**}	0.061	1	
11 Openness	0.084	-0.055	-0.110^{*}	-0.163^{**}	0.073	0.023	0.300^{**}	0.377^{**}	0.370^{**}	0.058	1

Note: This table presents pairwise correlations among the study's participant-level control variables ($N = 334$), including risk aversion, demographics, financial background measures, and Big Five personality traits. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6.3: Task Complexity and Information Quantity Predicting IV Calculation Accuracy (Conditions 7–9)

	(1)	(2)	(3)	(4)	(5)
Intercept	0.8486***	0.8472***	0.8472***	0.6782***	0.3770
	(26.178)	(27.715)	(27.682)	(5.056)	(1.549)
Complex	−0.0327***		−0.0339***	−0.0339***	−0.0339***
	(−5.611)		(−6.127)	(−6.108)	(−6.090)
Info_Quant		−0.0705***	−0.0705***	−0.0628***	−0.0621***
		(−3.281)	(−3.277)	(−2.934)	(−2.885)
Complex × Info_Quant			−0.0329***	−0.0329***	−0.0329***
			(−4.517)	(−4.503)	(−4.490)
Risk Aversion				−0.0080	−0.0021
				(−0.494)	(−0.116)
Gender				0.0293	0.0312
				(1.006)	(1.100)
Fin_edu				0.0032	−0.0047
				(0.146)	(−0.209)
Invest_Exp				0.0194	0.0185
				(0.638)	(0.609)
Fin_literacy				0.0269	0.0287
				(1.288)	(1.396)
Extraversion					0.0147
					(0.771)
Agreeableness					0.0001
					(0.004)
Conscientiousness					0.0244
					(0.819)
Neuroticism					0.0124
					(0.675)
Openness					0.0107
					(0.444)
Adj. R^2	0.065	0.078	0.117	0.122	0.126
Observations	840	840	840	840	840
Standard errors adjusted for clustering	Individual	Individual	Individual	Individual	Individual
Fixed effect (session)	Yes	Yes	Yes	Yes	Yes

Note: Dependent variable is participants' intrinsic-value (IV) calculation accuracy, estimated using the 5-minute time-constraint sample only (Conditions 7–9; $N = 168$). Column (1) includes only the task complexity trend. Column (2) includes only the information quantity trend. Column (3) includes both trends and their interaction (Complex × Info_Quant). Column (4) adds demographic covariates. Column (5) further includes the Big Five personality traits. All models include session fixed effects, and inference is based on participant-clustered (cluster-robust) t-statistics reported in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6.4: Task Complexity and Information Quantity Predicting Trading Decision Accuracy (Conditions 7–9)

	(1)	(2)	(3)	(4)	(5)
Intercept	0.7793^{***}	0.7773^{***}	0.7773^{***}	0.6568^{***}	0.2268
	(23.91)	(24.91)	(24.88)	(5.52)	(1.04)
Complex	-0.0496^{***}		-0.0508^{***}	-0.0508^{***}	-0.0508^{***}
	(-7.47)		(-8.04)	(-8.01)	(-7.99)
Info_Quant		-0.0949^{***}	-0.0949^{***}	-0.0884^{***}	-0.0848^{***}
		(-4.73)	(-4.73)	(-4.28)	(-4.09)
Complex × Info_Quant			-0.0345^{***}	-0.0345^{***}	-0.0345^{***}
			(-4.57)	(-4.55)	(-4.54)
Risk Aversion				-0.0043	-0.0012
				(-0.27)	(-0.07)
Gender				0.0005	0.0093
				(0.02)	(0.43)
Fin_edu				0.0068	-0.0099
				(0.35)	(-0.51)
Invest_Exp				0.0145	0.0063
				(0.44)	(0.20)
Fin_literacy				0.0303	0.0339^{*}
				(1.64)	(1.88)
Extraversion					0.0297
					(1.61)
Agreeableness					-0.0187
					(-0.73)
Conscientiousness					0.0361
					(1.27)
Neuroticism					0.0015
					(0.09)
Openness					0.0402^{*}
					(1.78)
Adj. R^2	0.092	0.102	0.162	0.165	0.179
Observations	840	840	840	840	840
Standard errors adjusted for clustering	Individual	Individual	Individual	Individual	Individual
Fixed effect (session)	Yes	Yes	Yes	Yes	Yes

Note: Dependent variable is trading-decision accuracy using the 5-minute time-constraint sample only (Conditions 7–9; $N = 168$). Column specifications are as in Table 6.3. All models include session fixed effects, and inference is based on participant-clustered (cluster-robust) t-statistics reported in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6.5: Task Complexity and Information Quantity Predicting Self-Rated Mental Effort (Conditions 7–9)

	(1)	(2)	(3)	(4)	(5)
Intercept	5.6980***	5.7048***	5.7048***	5.7466***	6.6382***
	(22.53)	(23.13)	(23.10)	(5.46)	(3.77)
Complex	0.1857***		0.1878***	0.1883***	0.1885***
	(6.25)		(6.35)	(6.33)	(6.30)
Info_Quant		0.3334*	0.3330*	0.3827**	0.3314*
		(1.83)	(1.83)	(2.02)	(1.80)
Complex × Info_Quant			0.0660*	0.0660*	0.0655*
			(1.91)	(1.90)	(1.88)
Risk Aversion				−0.0463	0.0326
				(−0.30)	(0.21)
Gender				−0.0916	−0.1773
				(−0.34)	(−0.69)
Fin_edu				0.2500	0.3416*
				(1.24)	(1.81)
Invest_Exp				0.1409	0.2576
				(0.42)	(0.74)
Fin_literacy				0.1831	0.1585
				(1.15)	(1.05)
Extraversion					0.1070
					(0.57)
Agreeableness					0.0715
					(0.26)
Conscientiousness					−0.0298
					(−0.12)
Neuroticism					0.2761
					(1.63)
Openness					−0.5656**
					(−2.46)
Adj. R^2	0.019	0.020	0.034	0.044	0.082
Observations	835	835	835	835	835
Standard errors adjusted for clustering	Individual	Individual	Individual	Individual	Individual
Fixed effect (session)	Yes	Yes	Yes	Yes	Yes

Note: Dependent variable is self-rated mental effort using the 5-minute time-constraint sample only (Conditions 7–9; $N = 168$). Column specifications are as in Table 6.3. All models include session fixed effects, and inference is based on participant-clustered (cluster-robust) t-statistics reported in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6.6: Time Constraint Effects on IV Calculation Accuracy (5 Minutes vs 3 Minutes)

	(1)	(2)	(3)	(4)	(5)
Intercept	0.7310***	0.7569***	0.7569***	0.6179***	0.3261*
	(14.85)	(18.00)	(17.97)	(5.96)	(1.95)
Complex	−0.0689***		−0.0668***	−0.0668***	−0.0668***
	(−8.74)		(−8.93)	(−8.92)	(−8.90)
Info_Quant		−0.1210***	−0.1210***	−0.1187***	−0.1174***
		(−4.78)	(−4.77)	(−4.67)	(−4.64)
Complex × Info_Quant			0.0095	−0.0424***	−0.0424***
			(0.86)	(−5.11)	(−5.10)
Time	0.1177**	0.0903*	0.0903*	0.0838	0.0908
	(2.00)	(1.74)	(1.73)	(1.48)	(1.58)
Time × Complex	0.0361***		0.0329***	0.0329***	0.0329***
	(3.68)		(3.54)	(3.53)	(3.53)
Time × Info_Quant		0.0505	0.0505	0.0552*	0.0513
		(1.52)	(1.52)	(1.68)	(1.55)
Time × Complex × Info_Quant			0.0095	0.0095	0.0095
			(0.86)	(0.86)	(0.86)
Risk Aversion				−0.0019	0.0009
				(−0.16)	(0.07)
Gender				0.0387	0.0378
				(1.57)	(1.60)
Fin_edu				0.0143	0.0079
				(0.85)	(0.49)
Invest_Exp				0.0473**	0.0470**
				(2.15)	(2.12)
Fin_literacy				0.0132	0.0096
				(0.95)	(0.69)
Extraversion					0.0288*
					(1.91)
Agreeableness					0.0168
					(0.84)
Conscientiousness					0.0096
					(0.48)
Neuroticism					0.0111
					(0.83)
Openness					0.0027
					(0.13)
Adj. R^2	0.194	0.194	0.255	0.261	0.269
Observations	1670	1670	1670	1670	1670
Standard errors adjusted for clustering	Individual	Individual	Individual	Individual	Individual
Fixed effect	Session	Session	Session	Session	Session

Note: Dependent variable is participants' intrinsic-value (IV) calculation accuracy. Column (1) includes task complexity, the Time indicator (5 minutes vs 3 minutes), and their interaction (Complexity × Time). Column (2) includes information quantity, Time, and their interaction (Information Quantity × Time). Column (3) includes both trends, Time, all two-way interactions (Complex × Info_Quant, Complexity × Time, Information Quantity × Time), and the three-way interaction (Complex × Info_Quant × Time). Column (4) adds demographic covariates. Column (5) further includes the Big Five personality traits. All models include session fixed effects, and inference is based on participant-clustered (cluster-robust) t-statistics reported in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6.7: Time Constraint Effects on Trading Decision Accuracy (5 Minutes vs 3 Minutes)

	(1)	(2)	(3)	(4)	(5)
Intercept	0.6262^{***}	0.6650^{***}	0.6650^{***}	0.6012^{***}	0.3321^{**}
	(8.94)	(11.91)	(11.90)	(5.86)	(2.06)
Complex	-0.0770^{***}		-0.0759^{***}	-0.0759^{***}	-0.0759^{***}
	(-10.31)		(-10.26)	(-10.25)	(-10.23)
Info_Quant		-0.1812^{***}	-0.1812^{***}	-0.1759^{***}	-0.1772^{***}
		(-8.13)	(-8.12)	(-7.75)	(-7.90)
Complex × Info_Quant			-0.0124	-0.0221^{**}	-0.0221^{**}
			(-1.06)	(-2.45)	(-2.45)
Time	0.1531^{**}	0.1123^{*}	0.1123^{*}	0.1059	0.1102
	(1.98)	(1.76)	(1.75)	(1.58)	(1.63)
Time × Complex	0.0274^{***}		0.0251^{**}	0.0251^{**}	0.0251^{**}
	(2.74)		(2.58)	(2.57)	(2.57)
Time × Info_Quant		0.0863^{***}	0.0863^{***}	0.0864^{***}	0.0890^{***}
		(2.88)	(2.87)	(2.90)	(3.02)
Time × Complex × Info_Quant			-0.0124	-0.0124	-0.0124
			(-1.06)	(-1.06)	(-1.06)
Risk Aversion				-0.0110	-0.0112
				(-0.97)	(-0.94)
Gender				0.0110	0.0151
				(0.54)	(0.75)
Fin_edu				0.0097	0.0028
				(0.56)	(0.17)
Invest_Exp				0.0197	0.0172
				(0.88)	(0.79)
Fin_literacy				0.0180	0.0155
				(1.40)	(1.22)
Extraversion					0.0238^{*}
					(1.65)
Agreeableness					-0.0172
					(-0.94)
Conscientiousness					0.0168
					(0.83)
Neuroticism					0.0115
					(0.92)
Openness					0.0293
					(1.54)
Adj. R^2	0.189	0.217	0.284	0.286	0.292
Observations	1670	1670	1670	1670	1670
Standard errors adjusted for clustering	Individual	Individual	Individual	Individual	Individual
Fixed effect	Session	Session	Session	Session	Session

Note: Dependent variable is trading-decision accuracy. Column specifications are as in Table 6.6. All models include session fixed effects, and inference is based on participant-clustered (cluster-robust) t-statistics reported in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6.8: Time Constraint Effects on Self-Rated Mental Effort (5 Minutes vs 3 Minutes)

	(1)	(2)	(3)	(4)	(5)
Intercept	5.8000***	5.6665***	5.6666***	4.7570***	4.5290***
	(11.83)	(11.93)	(11.92)	(5.76)	(3.31)
Complex	0.1689***		0.1667***	0.1661***	0.1657***
	(4.75)		(4.74)	(4.72)	(4.69)
Info_Quant		0.6230***	0.6224***	0.6554***	0.5817***
		(3.41)	(3.40)	(3.57)	(3.02)
Complex × Info_Quant			0.0242	0.0415	0.0412
			(0.45)	(0.99)	(0.99)
Time	−0.1020	0.0383	0.0381	−0.0638	−0.0081
	(−0.18)	(0.07)	(0.07)	(−0.12)	(−0.01)
Time × Complex	0.0169		0.0211	0.0220	0.0225
	(0.36)		(0.46)	(0.48)	(0.49)
Time × Info_Quant		−0.2895	−0.2894	−0.2869	−0.2428
		(−1.12)	(−1.12)	(−1.10)	(−0.90)
Time × Complex × Info_Quant			0.0242	0.0246	0.0245
			(0.45)	(0.45)	(0.45)
Risk Aversion				−0.0482	0.0126
				(−0.50)	(0.13)
Gender				0.1951	0.1099
				(0.90)	(0.52)
Fin_edu				−0.0331	0.0037
				(−0.25)	(0.03)
Invest_Exp				0.1484	0.2253
				(0.69)	(1.03)
Fin_literacy				0.1072	0.1026
				(1.19)	(1.16)
Extraversion					−0.0112
					(−0.09)
Agreeableness					0.0557
					(0.31)
Conscientiousness					0.0372
					(0.22)
Neuroticism					0.2692**
					(2.45)
Openness					−0.2965*
					(−1.77)
Adj. R^2	0.054	0.073	0.086	0.089	0.108
Observations	1640	1640	1640	1640	1640
Standard errors adjusted for clustering	Individual	Individual	Individual	Individual	Individual
Fixed effect	Session	Session	Session	Session	Session

Note: Dependent variable is self-rated mental effort. Column specifications are as in Table 6.6. All models include session fixed effects, and inference is based on participant-clustered (cluster-robust) t-statistics reported in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6.9: Robustness Check (Restricted sample): Time Effects on IV Calculation Accuracy

	(1)	(2)	(3)	(4)	(5)
Intercept	0.7736***	0.8093***	0.8093***	0.7559***	0.5488***
	(18.22)	(33.57)	(33.51)	(12.52)	(5.07)
Complex	−0.0691***		−0.0697***	−0.0697***	−0.0697***
	(−8.68)		(−11.24)	(−11.21)	(−11.19)
Info_Quant		−0.1429***	−0.1429***	−0.1384***	−0.1335***
		(−8.22)	(−8.20)	(−7.91)	(−7.29)
Complex × Info_Quant			0.0233***	−0.0564***	−0.0564***
			(2.63)	(−8.67)	(−8.65)
Time	0.1502***	0.1092***	0.1092***	0.0985***	0.1070***
	(3.21)	(3.58)	(3.58)	(3.19)	(3.26)
Time × Complex	0.0361***		0.0352***	0.0352***	0.0352***
	(3.80)		(4.50)	(4.49)	(4.48)
Time × Info_Quant		0.0699***	0.0699***	0.0674***	0.0637***
		(3.03)	(3.02)	(2.99)	(2.79)
Time × Complex × Info_Quant			0.0233***	0.0233***	0.0233***
			(2.63)	(2.62)	(2.62)
Risk Aversion				0.0071	0.0085
				(0.81)	(0.93)
Gender				−0.0102	−0.0103
				(−0.65)	(−0.67)
Fin_edu				−0.0064	−0.0105
				(−0.54)	(−0.91)
Invest_Exp				−0.0134	−0.0169
				(−0.90)	(−1.14)
Fin_literacy				0.0150	0.0168
				(1.38)	(1.55)
Extraversion					0.0160
					(1.61)
Agreeableness					0.0046
					(0.32)
Conscientiousness					0.0230
					(1.62)
Neuroticism					−0.0030
					(−0.37)
Openness					0.0043
					(0.30)
Adj. R^2	0.207	0.234	0.370	0.372	0.379
Observations	1180	1180	1180	1180	1180
Standard errors adjusted for clustering	Individual	Individual	Individual	Individual	Individual
Fixed effect	Session	Session	Session	Session	Session

Note: Dependent variable is participants' intrinsic-value (IV) calculation accuracy, estimated after excluding participants who recorded 0% IV accuracy (restricted sample; $N = 236$). Column specifications are as in Table 6.6. All models include session fixed effects, and inference is based on participant-clustered (cluster-robust) t-statistics reported in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6.10: Robustness Check (Restricted sample): Time Effects on Trading Decision Accuracy

	(1)	(2)	(3)	(4)	(5)
Intercept	0.6806^{***}	0.7295^{***}	0.7295^{***}	0.7177^{***}	0.4606^{***}
	(9.81)	(17.42)	(17.39)	(9.29)	(3.33)
Complex	-0.0834^{***}		-0.0839^{***}	-0.0839^{***}	-0.0839^{***}
	(-9.67)		(-11.03)	(-11.01)	(-10.98)
Info_Quant		-0.1956^{***}	-0.1956^{***}	-0.1934^{***}	-0.1853^{***}
		(-9.29)	(-9.28)	(-8.90)	(-8.34)
Complex × Info_Quant			0.0046	-0.0460^{***}	-0.0460^{***}
			(0.40)	(-5.29)	(-5.27)
Time	0.1563^{**}	0.0999^{**}	0.0999^{*}	0.0957^{*}	0.1051^{*}
	(2.09)	(1.97)	(1.97)	(1.83)	(1.94)
Time × Complex	0.0308^{***}		0.0295^{***}	0.0295^{***}	0.0295^{***}
	(2.79)		(2.97)	(2.96)	(2.95)
Time × Info_Quant		0.0895^{***}	0.0895^{***}	0.0854^{***}	0.0820^{***}
		(3.29)	(3.29)	(3.09)	(2.95)
Time × Complex × Info_Quant			0.0046	0.0046	0.0046
			(0.40)	(0.40)	(0.40)
Risk Aversion				0.0032	0.0015
				(0.30)	(0.14)
Gender				-0.0201	-0.0165
				(-1.21)	(-0.96)
Fin_edu				-0.0156	-0.0214
				(-1.15)	(-1.59)
Invest_Exp				-0.0103	-0.0181
				(-0.51)	(-0.94)
Fin_literacy				0.0034	0.0075
				(0.29)	(0.64)
Extraversion					0.0214^{*}
					(1.79)
Agreeableness					-0.0188
					(-1.18)
Conscientiousness					0.0315
					(1.58)
Neuroticism					-0.0038
					(-0.36)
Openness					0.0267
					(1.45)
Adj. R^2	0.171	0.212	0.324	0.323	0.332
Observations	1180	1180	1180	1180	1180
Standard errors adjusted for clustering	Individual	Individual	Individual	Individual	Individual
Fixed effect	Session	Session	Session	Session	Session

Note: Dependent variable is trading-decision accuracy, estimated after excluding participants who recorded 0% IV accuracy (restricted sample; $N = 236$). Column specifications are as in Table 6.6. All models include session fixed effects, and inference is based on participant-clustered (cluster-robust) t-statistics reported in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6.11: Robustness Check (Restricted sample): Time Effects on Self-Rated Mental Effort

	(1)	(2)	(3)	(4)	(5)
Intercept	5.4833***	5.3733***	5.3738***	4.7795***	4.7095***
	(10.59)	(10.71)	(10.69)	(5.40)	(2.78)
Complex	0.2432***		0.2429***	0.2426***	0.2422***
	(5.37)		(5.34)	(5.32)	(5.29)
Info_Quant		0.4403*	0.4380*	0.4843**	0.4186*
		(1.79)	(1.78)	(2.01)	(1.66)
Complex × Info_Quant			0.0240	0.0463	0.0462
			(0.36)	(0.83)	(0.83)
Time	0.0167	0.1424	0.1418	0.0378	0.0104
	(0.03)	(0.25)	(0.25)	(0.07)	(0.02)
Time × Complex	−0.0427		−0.0395	−0.0389	−0.0382
	(−0.78)		(−0.72)	(−0.70)	(−0.69)
Time × Info_Quant		−0.2210	−0.2193	−0.2128	−0.1799
		(−0.70)	(−0.69)	(−0.68)	(−0.55)
Time × Complex × Info_Quant			0.0240	0.0251	0.0248
			(0.36)	(0.38)	(0.37)
Risk Aversion				−0.1865*	−0.1392
				(−1.67)	(−1.25)
Gender				−0.0703	−0.0840
				(−0.29)	(−0.36)
Fin_edu				−0.0217	0.0014
				(−0.14)	(0.01)
Invest_Exp				0.1407	0.1851
				(0.54)	(0.70)
Fin_literacy				0.2309*	0.2049*
				(1.87)	(1.72)
Extraversion					0.1116
					(0.79)
Agreeableness					−0.0033
					(−0.01)
Conscientiousness					−0.0883
					(−0.45)
Neuroticism					0.2303*
					(1.69)
Openness					−0.1964
					(−0.93)
Adj. R^2	0.073	0.065	0.086	0.100	0.113
Observations	1170	1170	1170	1170	1170
Standard errors adjusted for clustering	Individual	Individual	Individual	Individual	Individual
Fixed effect	Session	Session	Session	Session	Session

Note: Dependent variable is self-rated mental effort, estimated after excluding participants who recorded 0% IV accuracy (restricted sample; $N = 236$). Column specifications are as in Table 6.6. All models include session fixed effects, and inference is based on participant-clustered (cluster-robust) t-statistics reported in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6.12: Time Constraint Effects on IV Accuracy, Trading Accuracy, and Mental Effort: Finance Professionals Sample

	No control variables			Including control variables					
	IV	DA	ME	IV	IV	DA	DA	ME	ME
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.4267***	0.4000***	7.2800***	0.3977*	0.8513**	0.1868	0.6384	6.0077***	0.0327
	(10.50)	(8.83)	(13.84)	(1.80)	(2.60)	(0.72)	(1.66)	(3.58)	(0.02)
Complex	−0.1194***	−0.0967***	0.2310**	−0.1194***	−0.1194***	−0.0967***	−0.0967***	0.2303**	0.2316**
	(−7.74)	(−5.95)	(2.64)	(−7.67)	(−7.60)	(−5.89)	(−5.84)	(2.63)	(2.62)
Time	0.2278**	0.1611	−0.3542	0.2323**	0.2779***	0.2035*	0.2455**	−0.0476	−0.3122
	(2.55)	(1.34)	(−0.40)	(2.39)	(2.88)	(1.87)	(2.19)	(−0.06)	(−0.42)
Time × Complex	0.0033	−0.0094	−0.0844	0.0033	0.0033	−0.0094	−0.0094	−0.0886	−0.0733
	(0.15)	(−0.41)	(−0.75)	(0.15)	(0.15)	(−0.41)	(−0.41)	(−0.78)	(−0.65)
Risk Aversion				−0.0147	−0.0149	−0.0394*	−0.0290	−0.1999	0.0870
				(−0.70)	(−0.64)	(−1.76)	(−1.15)	(−1.02)	(0.46)
Gender				−0.1003**	−0.1110**	−0.0369	−0.0282	−0.5640	−0.4362
				(−2.20)	(−2.48)	(−0.82)	(−0.54)	(−1.39)	(−1.21)
Fin_edu				−0.0346	−0.0399	−0.0325	−0.0260	−0.3060	−0.2807
				(−1.20)	(−1.28)	(−0.98)	(−0.66)	(−1.06)	(−1.20)
Invest_Exp				0.0170	−0.0148	0.0198	−0.0047	0.0126	0.4450**
				(0.49)	(−0.41)	(0.48)	(−0.11)	(0.04)	(2.05)
Fin_literacy				0.0104	0.0071	0.0473	0.0505	0.3804	0.4085**
				(0.35)	(0.24)	(1.54)	(1.64)	(1.60)	(2.04)
Extraversion					0.0152		0.0322		0.1253
					(0.62)		(1.16)		(0.53)
Agreeableness					0.0431		0.0046		0.2841
					(1.27)		(0.13)		(1.01)
Conscientiousness					−0.0185		−0.0238		−0.4199*
					(−0.57)		(−0.76)		(−1.92)
Neuroticism					−0.0391		−0.0214		0.7896***
					(−1.65)		(−0.80)		(4.74)
Openness					−0.0808***		−0.0780***		0.1360
					(−3.29)		(−2.79)		(0.65)
Adj. R^2	0.377	0.258	0.028	0.401	0.438	0.287	0.324	0.094	0.254
Observations	300	300	290	300	300	300	300	290	290
Standard errors adjusted for clustering	Individual	Individual	Individual	Individual	Individual	Individual	Individual	Individual	Individual
Fixed effect	Session	Session	Session	Session	Session	Session	Session	Session	Session

Note: Regressions are estimated using the finance-professional sample ($N = 60$). Dependent variables are intrinsic-value (IV) calculation accuracy, trading-decision accuracy (DA), and self-rated mental effort (ME). Columns (1)–(3) report baseline specifications without controls for IV, DA, and ME, respectively; each includes task complexity, the Time indicator (5 minutes vs 3 minutes), and their interaction (Complexity × Time). Columns (4), (6), and (8) add demographic and finance covariates (risk aversion, gender, financial education, investment experience, and financial literacy) for IV, DA, and ME, respectively. Columns (5), (7), and (9) further include the Big Five personality traits for the corresponding dependent variables. All models include session fixed effects, and inference is based on participant-clustered (cluster-robust) t-statistics reported in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6.13: Professional–Student Comparison of Decision Quality and Mental Effort Under High Time Pressure (Condition 3)

	No control variables			Including control variables					
	IV	DA	ME	IV	IV	DA	DA	ME	ME
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.4267***	0.4000***	7.2800***	0.3779*	0.3128	0.3732	0.8034**	5.9597***	6.3562***
	(10.53)	(8.85)	(13.87)	(1.92)	(0.91)	(1.65)	(2.36)	(4.80)	(2.97)
Complex	−0.1194***	−0.0967***	0.2314**	−0.1194***	−0.1194***	−0.0967***	−0.0967***	0.2362***	0.2360***
	(−7.76)	(−5.96)	(2.63)	(−7.71)	(−7.67)	(−5.92)	(−5.89)	(2.70)	(2.68)
Pro	0.0507	−0.0587	−0.3234	0.0756	0.0900	−0.0487	−0.0968	−0.1894	−0.4087
	(0.80)	(−0.90)	(−0.53)	(0.91)	(0.95)	(−0.57)	(−1.09)	(−0.30)	(−0.59)
Pro × Complex	0.0064	0.0053	−0.0003	0.0064	0.0064	0.0053	0.0053	−0.0068	−0.0074
	(0.35)	(0.27)	(−0.00)	(0.34)	(0.34)	(0.26)	(0.26)	(−0.06)	(−0.07)
Risk Aversion				−0.0057	−0.0020	−0.0388**	−0.0410*	−0.2779**	−0.1888
				(−0.30)	(−0.08)	(−2.11)	(−1.90)	(−2.13)	(−1.39)
Gender				−0.0230	−0.0275	0.0115	0.0350	0.4420	0.4024
				(−0.51)	(−0.57)	(0.27)	(0.77)	(1.17)	(1.04)
Fin_edu				−0.0054	−0.0153	−0.0223	−0.0068	−0.1171	−0.0794
				(−0.20)	(−0.54)	(−0.80)	(−0.21)	(−0.61)	(−0.35)
Invest_Exp				0.0041	0.0011	−0.0033	−0.0232	0.1154	0.1089
				(0.12)	(0.03)	(−0.09)	(−0.59)	(0.50)	(0.43)
Fin_literacy				0.0151	0.0010	0.0124	0.0135	0.1638*	0.1763
				(0.80)	(0.05)	(0.62)	(0.64)	(1.76)	(1.52)
Extraversion					0.0464		0.0328		0.0493
					(1.54)		(1.19)		(0.22)
Agreeableness					0.0456		−0.0159		−0.0642
					(1.07)		(−0.41)		(−0.23)
Conscientiousness					−0.0243		−0.0498		−0.1440
					(−0.61)		(−1.17)		(−0.58)
Neuroticism					−0.0049		−0.0260		0.1728
					(−0.17)		(−1.00)		(0.77)
Openness					−0.0381		−0.0181		−0.0799
					(−1.00)		(−0.54)		(−0.35)
Adj. R^2	0.321	0.202	0.089	0.317	0.327	0.215	0.224	0.127	0.128
Observations	450	450	427	450	450	450	450	427	427
Standard errors adjusted for clustering	Individual	Individual	Individual	Individual	Individual	Individual	Individual	Individual	Individual
Fixed effect	Session	Session	Session	Session	Session	Session	Session	Session	Session

Note: Regressions are estimated on the pooled sample of finance professionals and students who completed Condition 3 (3-minute per question time constraint), with a Professional indicator distinguishing finance professionals from students. Dependent variables are intrinsic-value (IV) calculation accuracy, trading-decision accuracy (DA), and self-rated mental effort (ME). Columns (1)–(3) report baseline specifications without controls for IV, DA, and ME, respectively; each includes the task complexity trend, the Professional indicator, and their interaction (Professional × Complexity). Columns (4), (6), and (8) add demographic and finance covariates for IV, DA, and ME, respectively. Columns (5), (7), and (9) further include the Big Five personality traits. All models include session fixed effects, and inference is based on participant-clustered (cluster-robust) t-statistics reported in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6.14: Professional–Student Comparison of Decision Quality and Mental Effort Under Low Time Pressure (Condition 9)

	No control variables			Including control variables					
	IV	DA	ME	IV	IV	DA	DA	ME	ME
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.6436***	0.6128***	6.7858***	0.1950	0.1454	0.1401	0.0367	6.5424***	6.7338**
	(12.21)	(11.74)	(15.54)	(0.82)	(0.41)	(0.55)	(0.10)	(2.95)	(2.27)
Complex	−0.1161***	−0.1061***	0.1467**	−0.1161***	−0.1161***	−0.1061***	−0.1061***	0.1455**	0.1617**
	(−7.57)	(−6.61)	(2.10)	(−7.53)	(−7.48)	(−6.57)	(−6.53)	(2.04)	(2.33)
Pro	0.0710	0.0893	−0.5983	0.2069**	0.2037**	0.2192**	0.2157**	−0.0786	−0.1349
	(0.82)	(1.11)	(−0.91)	(2.06)	(2.11)	(2.28)	(2.21)	(−0.09)	(−0.16)
Pro × Complex	0.0504**	0.0333	0.1201	0.0504**	0.0504**	0.0333	0.0333	0.1191	0.1017
	(2.55)	(1.65)	(1.36)	(2.54)	(2.52)	(1.64)	(1.63)	(1.33)	(1.15)
Risk Aversion				−0.0141	−0.0186	−0.0136	−0.0171	0.2647	0.3237*
				(−0.61)	(−0.76)	(−0.66)	(−0.79)	(1.29)	(1.67)
Gender				−0.0392	−0.0303	−0.0219	−0.0107	−0.8425**	−0.7865***
				(−1.02)	(−0.79)	(−0.67)	(−0.29)	(−2.43)	(−2.70)
Fin_edu				−0.0396	−0.0343	−0.0431	−0.0374	−0.0304	0.0521
				(−1.35)	(−1.13)	(−1.66)	(−1.31)	(−0.10)	(0.19)
Invest_Exp				0.0765**	0.0871**	0.0793*	0.0938**	−0.0825	−0.0809
				(2.10)	(2.22)	(1.98)	(2.18)	(−0.23)	(−0.23)
Fin_literacy				0.0497	0.0520	0.0455	0.0470	0.1664	0.0703
				(1.64)	(1.65)	(1.66)	(1.65)	(0.84)	(0.36)
Extraversion					0.0195		0.0171		−0.2555
					(0.61)		(0.63)		(−1.23)
Agreeableness					−0.0068		−0.0018		0.3215
					(−0.18)		(−0.05)		(0.96)
Conscientiousness					−0.0226		−0.0273		−0.2492
					(−0.65)		(−0.81)		(−0.99)
Neuroticism					0.0015		0.0104		0.5507***
					(0.06)		(0.43)		(2.91)
Openness					0.0200		0.0234		−0.3440
					(0.62)		(0.74)		(−1.24)
Adj. R^2	0.152	0.176	0.056	0.189	0.185	0.202	0.198	0.104	0.175
Observations	420	420	417	420	420	420	420	417	417
Standard errors adjusted for clustering	Individual	Individual	Individual	Individual	Individual	Individual	Individual	Individual	Individual
Fixed effect	Session	Session	Session	Session	Session	Session	Session	Session	Session

Note: Regressions are estimated using the pooled professional–student sample in Condition 9 (5-minute per question time constraint). Column specifications are as in Table 6.13. All models include session fixed effects, and inference is based on participant-clustered (cluster-robust) t-statistics reported in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6.15: Robustness check: Original and entropy-balanced estimates for Study 3

	IV accuracy		Trading accuracy		Mental effort	
	Original	Entropy	Original	Entropy	Original	Entropy
Complex	-0.0668***	-0.0712***	-0.0759***	-0.0779***	0.1657***	0.1746***
	(-8.90)	(-7.82)	(-10.23)	(-7.98)	(4.69)	(3.79)
Info_Quant	-0.1174***	-0.0991***	-0.1772***	-0.1727***	0.5817***	0.6731***
	(-4.64)	(-3.08)	(-7.90)	(-6.63)	(3.02)	(2.91)
Time (5 min)	0.0430	0.0732	0.0565	0.1140**	0.0580	0.2313
	(1.03)	(1.20)	(1.11)	(2.16)	(0.14)	(0.45)
Complex × Time	0.0329***	0.0402***	0.0251**	0.0347***	0.0225	0.0242
	(3.52)	(3.43)	(2.57)	(2.80)	(0.49)	(0.41)
Info_Quant × Time	0.0513	0.0367	0.0890***	0.0907***	-0.2428	-0.2410
	(1.55)	(0.91)	(3.02)	(2.73)	(-0.90)	(-0.70)
Complex × Info_Quant	-0.0424***	-0.0497***	-0.0221**	-0.0175	0.0412	0.0256
	(-5.10)	(-5.08)	(-2.45)	(-1.57)	(0.99)	(0.50)
Complex × Info_Quant × Time	0.0095	0.0081	-0.0124	-0.0254*	0.0245	0.0681
	(0.86)	(0.61)	(-1.05)	(-1.70)	(0.45)	(1.04)
Risk Aversion	0.0009	-0.0096	-0.0112	-0.0199	0.0126	0.1622
	(0.07)	(-0.68)	(-0.94)	(-1.58)	(0.13)	(1.44)
Gender	0.0378	0.0290	0.0151	-0.0025	0.1099	0.2416
	(1.60)	(0.95)	(0.75)	(-0.08)	(0.52)	(0.89)
Fin_edu	-0.0079	-0.0039	-0.0028	0.0069	-0.0037	0.1223
	(-0.49)	(-0.19)	(-0.17)	(0.40)	(-0.03)	(0.66)
Invest_Exp	0.0470**	0.0369	0.0172	0.0018	0.2253	0.3669
	(2.12)	(1.43)	(0.79)	(0.08)	(1.03)	(1.62)
Fin_literacy	0.0096	0.0027	0.0155	0.0136	0.1026	0.0929
	(0.69)	(0.17)	(1.22)	(0.82)	(1.16)	(0.86)
Extraversion	0.0288*	0.0383**	0.0238*	0.0370**	-0.0112	0.0416
	(1.91)	(2.14)	(1.65)	(2.20)	(-0.09)	(0.28)
Agreeableness	0.0168	-0.0193	-0.0172	-0.0467**	0.0557	0.3315
	(0.84)	(-0.78)	(-0.94)	(-2.16)	(0.31)	(1.29)
Conscientiousness	0.0096	0.0062	0.0168	0.0215	0.0372	-0.1722
	(0.48)	(0.24)	(0.83)	(0.83)	(0.22)	(-0.80)
Neuroticism	0.0111	0.0144	0.0115	0.0102	0.2692**	0.1369
	(0.83)	(0.92)	(0.92)	(0.66)	(2.45)	(0.93)
Openness	0.0027	-0.0023	0.0293	0.0103	-0.2965*	-0.1166
	(0.13)	(-0.09)	(1.54)	(0.43)	(-1.77)	(-0.51)
Adj. R^2	0.269	0.302	0.292	0.331	0.108	0.147
Observations	1670	1625	1670	1625	1640	1595
Standard errors adjusted for clustering	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effect (session)	Yes	Yes	Yes	Yes	Yes	Yes
Participant controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports OLS regressions at the task level for Study 3. The original specifications use the full student analysis sample. Entropy-balanced specifications include participants identifying as male or female. Female participants are reweighted to match male participants on financial education, investment experience, and financial literacy. The entropy weights are constructed at the participant level and the same weight is applied to all five repeated observations. The original participant controls and session fixed effects are retained, with standard errors clustered at the participant level. Clustered t-statistics appear in parentheses. Zero-coded missing mental-effort responses are excluded. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Chapter 7

Conclusion

7.1 Returning to the aim of the thesis

This thesis set out to explain how features of the information environment shape the quality of investor decisions and perceived mental effort in a controlled financial decision-making setting. More specifically, it examines whether information quantity, task complexity, irrelevant data, and time constraints affect the accuracy of intrinsic value calculation, trading decisions, and self-rated mental effort. The broader motivation is that financial markets are often discussed as if the presence of relevant information is enough to support sound judgement. Yet both behavioural finance and cognitive psychology suggest that this assumption is too simple. Investors do not process information under frictionless conditions. They face finite attention, limited working memory, and time limits, so the value of information depends not only on what is available, but also on whether the decision environment allows that information to be processed effectively (Baddeley & Hitch, 1974; DellaVigna & Pollet, 2009; Hirshleifer et al., 2009; Paas et al., 2003; Peng, 2005; Peng & Xiong, 2006; Sims, 2003; Sweller, 1988).

Seen in that light, the central argument of the thesis is straightforward. Investor performance depends not only on what information is provided, but also on whether that information can be screened, organised, integrated, and translated into action under realistic cognitive constraints. When the information set expands, when the task becomes more complex, when irrelevant cues compete for attention, or when time becomes scarce, decision quality may weaken even though all relevant information remains visible. The thesis therefore does not challenge the importance of information in financial decision-making. Instead, it qualifies the simpler assumption that more information will necessarily improve judgement. Information is useful only to the extent that decision makers can actually process it.

This argument links directly back to the three research questions set out in Chapter 1. The first asks how information quantity and task complexity affect performance and mental effort. The second asks whether clearly irrelevant data changes those outcomes. The third asks whether a more relaxed time condition weakens the adverse effects of information quantity and task complexity. Taken together, the results provide a coherent answer. Information burden matters, but it is not best understood as a single undifferentiated condition. Different sources of burden operate through somewhat different channels and carry different implications for performance and experience.

7.2 Synthesis of the main findings

The first main conclusion of the thesis is that information quantity and task complexity are the two most consistent and substantively important pressures on investor judgement. Study 1 shows that both factors reduce intrinsic value calculation accuracy and trading decision accuracy, while increasing self-rated mental effort. These effects are not merely statistically detectable. They are economically meaningful. As the information set expands, participants have more cues to screen, more intermediate steps to compute, and more opportunities to make mistakes. As task complexity rises, they have to coordinate more elements and manage greater interdependence across steps. Under these conditions, both forms of objective performance decline in a clear and monotonic way, while perceived effort increases.

Just as importantly, the effects of information quantity and task complexity are not simply additive for objective performance. The penalty from one becomes steeper as the other increases. In other words, the cost of greater complexity is higher when the information environment is already dense, and the cost of additional information is higher when the task itself is already demanding. That compounding pattern is evident in intrinsic value calculations and trading decisions, whereas self-rated mental effort rises in a more nearly additive fashion. This distinction matters. It suggests that participants recognised the growing burden of the task, but the deterioration in performance accelerated more sharply than their subjective effort ratings alone would imply. In practical terms, demanding financial environments do not merely feel harder. They also become disproportionately harder to perform well in once multiple demands accumulate.

The second main conclusion is that irrelevant data matters, but not in exactly the same way as information quantity and task complexity. Study 2 introduces clearly non-diagnostic firm information in order to capture a more realistic information environment, one in which investors are not presented with perfectly curated material. The results reveal a more complex pattern than those in Study 1. Once the core burdens of information quantity and task complexity are taken into account, irrelevant data do not produce the same strong and consistent decline in objective accuracy. At the midpoint of the design, the accuracy effect is modest and varies across the wider load environment. In lower-load settings, irrelevant cues appeared more damaging. In denser settings, that penalty weakens and sometimes disappears.

By contrast, the effect on self-rated mental effort is clearer. Irrelevant information makes the task feel more effortful, especially when the information set is sparse to moderate. This suggests that irrelevant data should not simply be treated as another instance of quantity. Quantity refers to how much information must be processed. Irrelevance refers to the fact that some material must also be screened and discounted. In the present setting, that extra screening burden appears more reliably in participants' reported effort than in final accuracy outcomes. This finding matters because it clarifies how different forms of information burden affect decision-making in different ways. Information burden arises not only because there is more to process, but also because some of what is presented competes for attention without improving the decision.

The third main conclusion is that time constraint mainly changes how harmful the other burdens become, rather than acting as a simple uniform shift in all outcomes. Study 3 shows that the tighter three-minute regime is most costly in the high-demand region of the design. Under the more relaxed five-minute condition, performance improves most clearly where task complexity and information quantity are already high. For intrinsic value calculation accuracy, additional time flattens the complexity gradient. For trading decision accuracy, additional time reduces the penalty associated with greater information quantity. The direct time effect at the midpoint of the design is more modest, and the effect on self-rated mental effort is weaker than the effect on objective performance.

This pattern is theoretically informative. It suggests that time pressure does not simply make the task feel uniformly harder. Rather, it seems to impair performance by reducing the opportunity for verification, fuller search, and careful integration when the task is already cognitively demanding. Time therefore operates as part of the cognitive environment, not merely as a procedural detail. Its importance becomes most visible when other sources of burden are already pressing on limited processing capacity.

A fourth conclusion comes from the professional comparison and external validity analysis. Overall, the professional sample reproduces the broad mechanism at the centre of the thesis. Across both students and professionals, greater task complexity remains costly, and more demanding tasks are associated with lower performance and higher perceived burden. At the same time, the comparison suggests that expertise becomes more visible when the environment provides room for it to be expressed. Under tighter time pressure, students and professionals look more similar. Under the more relaxed time condition, professionals perform better, especially in overall accuracy, and appear better able to use additional time for checking and verification. A more cautious interpretation is therefore warranted. The thesis does not suggest that students and professionals are the same. Instead, the results indicate that the core cognitive mechanism identified here is unlikely to be simply a product of using a less experienced sample.

7.3 What these findings mean in relation to the literature

In general, the findings align with the literature reviewed in Chapters 1 and 2. First, they support the behavioural finance view that investor attention is limited, selective, and costly. Much of that literature infers attentional constraints indirectly from market-level outcomes, such as weaker responses to earnings announcements released at low-attention times or when multiple firms compete for attention simultaneously (DellaVigna & Pollet, 2009; Hirshleifer et al., 2009). The present thesis complements that work by showing, at the level of the individual decision maker, how judgement changes when the demands of a financial task are manipulated directly. In this sense, the thesis brings the mechanism into clearer view. It shows not only that attention matters, but also which features of the decision environment appear to bind most clearly.

Second, the findings are consistent with rational inattention arguments, in which decision makers allocate scarce processing capacity selectively rather than processing all available information with equal precision (Peng, 2005; Peng & Xiong, 2006; Sims, 2003). This point is especially important because the design was constructed to reduce the usual information-value confound. Higher-quantity conditions did not provide qualitatively better information. Instead, they required participants to process more structurally equivalent information in order to make the same type of decision. That feature allows the thesis to say more confidently that the observed deterioration reflects processing burden rather than a change in informational usefulness.

Third, the findings support the relevance of working memory and Cognitive Load Theory for understanding financial judgement (Baddeley & Hitch, 1974; Paas et al., 2003; Sweller, 1988). Information quantity and task complexity behaved in ways that are consistent with limits on working memory capacity. The compounding losses in Study 1 fit the idea that multiple forms of intrinsic demand can jointly move decision makers closer to overload. Study 2 then suggests that irrelevant information behaves more like extraneous demand, increasing the burden of processing even when the effect on final performance is less consistent. Study 3 adds that the time constraint intensifies these pressures by reducing the scope for fuller integration and error-checking. Together, these patterns suggest that financial decision-making can be better understood when the informational environment is treated as part of the mechanism rather than as background.

The differential time effects in Study 3 also provide a useful implication for rational inattention. In rational-inattention models, investors face a finite information-processing capacity and must allocate that capacity selectively across competing signals (Sims, 2003; Peng, 2005; Peng & Xiong, 2006). The present results suggest that this allocation problem depends not only on the amount and complexity of information, but also on the time available to process it. Additional time provides relatively little benefit when processing demands are low, but becomes more valuable when tasks are complex or information intensive. This pattern is consistent with the idea that time relaxes an effective capacity constraint, allowing investors to allocate greater attention to processing, integration, and verification where the marginal value of additional processing is highest. Conversely, under tighter time constraints, investors may need to economise on attention more aggressively, process signals with lower precision, or rely on simplified decision strategies.” The findings therefore suggest that capacity allocation in rational inattention settings is partly time dependent rather than determined by information quantity alone.

7.4 Original contribution and significance of the thesis

This thesis makes several contributions.

First, it contributes to behavioural finance by providing direct individual-level evidence on how cognitive constraints shape financial judgement. Much of the existing finance literature identifies limited attention through market responses, disclosure timing, or aggregate behaviour. By contrast, the present thesis observes how intrinsic value calculation accuracy, trading decision accuracy, and perceived mental effort change when the demands of a financial task are manipulated systematically in a controlled experimental setting.

Second, it contributes to the information-overload literature by separating information quantity from information value. A recurring problem in that literature is that more information often also means more potentially useful information, which makes it difficult to identify whether poorer performance reflects overload or a different decision problem. The present design addresses that issue by defining information quantity as the amount of structurally equivalent information that must be processed to reach the same type of decision. This design choice matters because it makes it more plausible that the observed performance losses reflect processing burden itself.

Third, the thesis contributes to the dialogue between finance and cognitive psychology. It shows that concepts such as working memory, intrinsic load, and extraneous load offer a clearer mechanism for understanding why investor judgement may deteriorate when financial tasks become dense, complex, distracting, or rushed. In that respect, the thesis moves beyond a broad appeal to distraction alone and offers a more differentiated account of how informational demands operate.

Fourth, the thesis develops a more precise account of information burden. One of the clearest implications of the full set of results is that information burden should not be treated as a single broad condition. Information quantity, task complexity, irrelevant data, and time constraint all matter, but they do not matter in exactly the same way. Information quantity and task complexity directly weaken accuracy and raise effort. Irrelevant data raises effort more consistently than it lowers performance. Time mainly alters how strongly the other pressures translate into lower performance. This distinction is important because it suggests that overload is better understood as a family of related but analytically distinct pressures.

Finally, the thesis has practical significance. It suggests that decision usefulness depends not only on whether information is disclosed, but also on whether the information environment is cognitively manageable enough to support its effective use. In modern financial settings, where disclosure volume and data availability continue to expand, this is not a minor issue. It bears directly on how information should be structured, presented, and timed if it is to support sound judgement.

7.5 Implications for research and practice

The findings have several implications for finance research. They suggest that accounts of investor behaviour should pay closer attention to the cognitive structure of the decision environment. Markets may be information-rich, yet individual decision makers still face limited capacity to process that information accurately. This means that informational efficiency is partly a question of cognitive manageability, not only informational availability.

The findings also carry implications for disclosure design. More extensive disclosure is not automatically more useful. Longer or denser information sets may, in principle, reduce uncertainty, but in practice they can also increase the burden of screening, integration, and verification. This does not imply that firms should disclose less in a simplistic sense. It does suggest that clearer organisation, better prioritisation of diagnostic information, and reduced irrelevant detail may matter for decision usefulness.

For investor education, the results imply that technical knowledge alone may be insufficient. Investors may also benefit from strategies that help them prioritise information, manage complex multi-step tasks, screen out non-diagnostic cues, and work effectively under time limits. The issue is not only whether an investor understands a valuation model. It is whether that model can still be used accurately when the information environment becomes dense and demanding.

For investor-facing platforms and information intermediaries, the thesis suggests that presentation matters. Better outcomes may require interfaces and communication practices that reduce unnecessary burden, support more structured processing, and avoid forcing users to work under avoidably compressed time conditions when the task is already complex.

These findings are also relevant to regulatory approaches that seek to make financial disclosure more usable for non-expert investors. In New Zealand, for example, the Financial Markets Conduct Regulations 2014 require Product Disclosure Statements to include a Key Information Summary designed to present the most significant aspects of an investment offer for a prudent but non-expert person, and the regulations impose limits on the length of these summaries. Such requirements are consistent with the present findings because they recognise that decision usefulness depends not only on whether information is disclosed, but also on whether investors can identify and process the most decision-relevant information efficiently. The results of this thesis therefore support disclosure approaches that prioritise diagnostic information, use layered or summary formats, and reduce unnecessary processing demands while preserving access to fuller information for investors who require it. In this sense, streamlined disclosure should not be interpreted as simply providing less information, but as structuring information so that the most relevant material can be processed more effectively.

7.6 Limitations of the thesis

These conclusions should be interpreted in light of several limitations. First, the thesis relies primarily on student participants from Vietnamese universities. Although this is appropriate for identifying general behavioural mechanisms, and although the professional comparison provides a useful external check, student samples cannot fully capture the institutional experience, incentives, and market exposure of professional investors.

Second, the research uses a controlled laboratory valuation and trading task. That control is a strength for causal identification, but it also means that some features of real financial environments are necessarily abstracted away. Real markets involve dynamic information arrival, richer forms of uncertainty, emotional salience, social influence, and feedback from realised outcomes. The present setting cannot fully reproduce these features.

Third, the time manipulation compares two specific regimes, three minutes and five minutes per question. This is sufficient to identify an important timing effect, but it does not exhaust the many ways in which time pressure may operate in real financial environments.

Fourth, the irrelevant-data manipulation takes one specific form, namely clearly non-diagnostic quantitative firm attributes. Other forms of irrelevance, especially narrative, visual, persuasive, or ambiguously related content, may operate differently and perhaps more strongly. The present results should therefore be interpreted as evidence for one important type of irrelevant information rather than as a complete account of all forms of informational distraction.

Fifth, self-rated mental effort is a useful and well-established measure of subjective burden, but it does not capture every aspect of processing. Some strategic adjustments, such as narrower search or earlier stopping, may not be fully reflected in self-reports. For that reason, the effort results should be read as an informative but partial indicator of the cognitive demands imposed by the task.

Taken together, these limitations do not weaken the core contribution of the thesis, but they do define the boundaries within which the findings should be interpreted. They also point clearly to the next stage of research, especially the value of testing the present mechanisms in broader samples, richer decision settings, and with a wider range of measures.

7.7 Directions for future research

Several useful directions follow from these limitations. One extension would be to examine more dynamic financial tasks in which information arrives sequentially and participants choose how much to inspect before acting. This would bring the experimental setting closer to real investment environments, where attention must often be allocated across unfolding information streams rather than fixed bundles of information. It would also allow future studies to observe more directly how investors adapt their search and stopping behaviour as task demands change over time.

A second direction would be to test other forms of irrelevant information, including narrative disclosures, visually salient cues, emotionally engaging material, or content that is only ambiguously related to the task. These forms of irrelevance may be harder to screen out than the clearly non-diagnostic numeric cues used in the present thesis. Exploring these variations would help clarify whether the main effect of irrelevance continues to lie primarily in increased mental effort, or whether some forms of irrelevant information have stronger consequences for decision accuracy.

A third direction would be to expand the sample in future research. Including larger professional samples and a wider range of participant backgrounds would provide a stronger test of the external validity and generalisability of the present findings. In particular, future studies could include participants from different institutional roles, levels of expertise, and market contexts in order to assess whether the cognitive mechanisms identified in this thesis operate similarly across different groups of decision makers. A broader sample would also make it possible to examine more carefully whether expertise, professional background, or market experience moderates the effects of information quantity, task complexity, irrelevant data, and time constraint.

A fourth direction would be to combine subjective effort ratings with more direct process measures, such as response times, information search behaviour, eye tracking, or physiological indicators. This would allow future work to observe more directly how participants adapt their strategies as information quantity, complexity, irrelevance, and time constraint change. Such evidence would complement the outcome-based measures used in the present thesis and help clarify whether lower performance reflects reduced search, earlier stopping, weaker integration, or greater susceptibility to distraction.

A fifth direction would be to investigate whether particular forms of summarisation, disclosure design, or decision support can reduce cognitive burden without reducing informational usefulness. This would speak directly to the applied issue raised by the thesis, namely how financial information can be made not only available, but genuinely usable. In that sense, future research could move beyond documenting the effects of cognitive burden and begin to examine more directly how those effects might be mitigated in practice.

7.8 Final concluding statement

The central message of this thesis is clear. Financial decision quality depends not only on what information investors receive, but also on the cognitive conditions under which that information must be processed. More information is not always better. Greater complexity is not merely an inconvenience. Irrelevant information can impose real effort costs even when its effect on final accuracy is limited. Additional time can materially improve performance, especially when the task is already demanding.

By bringing together behavioural finance and cognitive psychology, this thesis offers a more realistic account of how investors use information and why judgement may weaken in dense and demanding financial environments. Its broader implication is that informational efficiency is partly a question of cognitive manageability. Information has value only to the extent that decision makers can actually process it. That, ultimately, is the main conclusion of this thesis.

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Appendix

Appendix A: Ethics Approval

Auckland University of Technology Ethics Committee (AUTEC)

Auckland University of Technology, D-88, Private Bag 92006, Auckland 1142, New Zealand.
T: +64 9 921 9999 ext. 8316 E: `ethics@aut.ac.nz` `www.aut.ac.nz/researchethics`

28 May 2024

Nhut (Nick) Nguyen
Faculty of Business Economics and Law

Dear Nhut (Nick)

Re Ethics Application: 24/124 The limit of an investor's capacity to process information

Thank you for your responses to AUTEC's conditions.

Your ethics application has been approved for three years until 27 May 2027.

Standard Conditions of Approval

1. The research is to be undertaken in accordance with the Auckland University of Technology Code of Conduct for Research and as approved by AUTEC.
2. All public facing documents must have the AUTEC approval number and be of a high standard of spelling and grammar. Dates on the Information Sheet(s) and Consent Form(s) must be consistent.
3. Any amendments to the project must be approved by AUTEC prior to being implemented.
4. A progress report is due annually on the anniversary of the approval date.
5. A final report is due at the expiration of the approval period, or, upon completion of project.
6. Any serious or adverse events must be reported to AUTEC, this includes unforeseen issues that might affect continued ethical acceptability of the project.
7. AUTEC grants ethical approval only. You are responsible for obtaining management permission for access from any institution or organisation at which your research is being conducted and you need to meet all ethical, legal, public health, and locality obligations or requirements for the jurisdictions in which the research is being undertaken.

The application number and title need to be referenced on all correspondence related to this project.

All forms are available online: `http://www.aut.ac.nz/research/researchethics`

For any enquiries, please contact `ethics@aut.ac.nz`

(This is a computer-generated letter for which no signature is required)

The AUTEC Secretariat
Auckland University of Technology Ethics Committee

Cc: `Ryq2651@autuni.ac.nz`; `james.phillips@aut.ac.nz`; Saten Kumar

Auckland University of Technology Ethics Committee (AUTEC)

Auckland University of Technology, Private Bag 92006, Auckland 1142, New Zealand.
T: +64 9 921 9999 ext. 8316 E: ethics@aut.ac.nz www.aut.ac.nz/researchethics

11 September 2024

Nhut (Nick) Nguyen
Faculty of Business Economics and Law

Dear Nhut (Nick)

Re: Ethics Application: 24/124 The limit of an investor's capacity to process information

Thank you for your responses to the conditions for the amendment to your ethics application.

The amendment to the recruitment protocol (location) has been approved.

Standard Conditions of Approval

1. The research is to be undertaken in accordance with the Auckland University of Technology Code of Conduct for Research and as approved by AUTEC.
2. All public facing documents must have the AUTEC approval number and be of a high standard of spelling and grammar. Dates on the Information Sheet(s) and Consent Form(s) must be consistent.
3. Any amendments to the project must be approved by AUTEC prior to being implemented.
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The application number and title need to be referenced on all correspondence related to this project.

All forms are available online: http://www.aut.ac.nz/research/researchethics

For any enquiries, please contact ethics@aut.ac.nz

(This is a computer-generated letter for which no signature is required)

The AUTEC Secretariat
Auckland University of Technology Ethics Committee

Cc: Ryq2651@autuni.ac.nz; james.phillips@aut.ac.nz; Saten Kumar

Auckland University of Technology Ethics Committee (AUTEC)

Auckland University of Technology, Private Bag 92006, Auckland 1142, New Zealand.
ethics@aut.ac.nz   www.aut.ac.nz/researchethics

7 May 2025

Nhut (Nick) Nguyen
Faculty of Business Economics and Law

Dear Nhut (Nick)

Re: Ethics Application: 24/124 The limit of an investor's capacity to process information

The amendment to the recruitment and data collection protocols (*stop collecting data from students for conditions 10–12; include another group of participants (professional investors from Yuana Securities); use an updated set of conditions to collect data from the investment professionals*) have been approved.

Non-Standard Conditions of Approval

1. Advise in the PIS that they can withdraw by exiting the survey at any time by closing the browser.

Non-standard conditions do not need to be submitted to or reviewed by AUTEC unless requested but must be completed before commencing your study.

Standard Conditions of Approval

1. The research is to be undertaken in accordance with the Auckland University of Technology Code of Conduct for Research and as approved by AUTEC.
2. All public facing documents must have the AUTEC approval number and be of a high standard of spelling and grammar. Dates on the Information Sheet(s) and Consent Form(s) must be consistent.
3. Any amendments to the project must be approved by AUTEC prior to being implemented.
4. A progress report is due annually on the anniversary of the approval date.
5. A final report is due at the expiration of the approval period, or, upon completion of project.
6. Any serious or adverse events must be reported to AUTEC, this includes unforeseen issues that might affect continued ethical acceptability of the project.
7. AUTEC grants ethical approval only. You are responsible for obtaining management permission for access from any institution or organisation at which your research is being conducted and you need to meet all ethical, legal, public health, and locality obligations or requirements for the jurisdictions in which the research is being undertaken.

The application number and title need to be referenced on all correspondence related to this project.

All forms are available online: http://www.aut.ac.nz/research/researchethics

For any enquiries, please contact the Secretariat at ethics@aut.ac.nz

(This is a computer-generated letter for which no signature is required)

The AUTEC Secretariat
Auckland University of Technology Ethics Committee

Cc: `Ryq2651@autuni.ac.nz`; `james.phillips@aut.ac.nz`; Saten Kumar

Appendix B1: Participant Information Sheet (English)

Date Information Sheet Produced: 23/05/2024

Project Title

The limit of an investor's capacity to process information.

An Invitation

My name is Thang Nguyen, and I am a PhD student in the Finance Department at AUT. I am writing to request your participation in a stock analysis game and a survey about individual characteristics. Participants will get a $10 gift card and be eligible to win a $100 voucher in a random draw.

What is the purpose of this research?

This research seeks to examine the decision-making process of financial investors. I am interested in looking at how the quality of financial decisions is influenced by different information characteristics, the time provided to make decisions, and an individual's attributes. I also want to see how the interplay of these factors affects investors' decision-making process and trading outcomes.

This research is being undertaken as a requirement of my Ph.D. The findings of this research may be used for academic publications and presentations.

How was I identified and why am I being invited to participate in this research?

You responded to a flyer advertising the study and scanned the QR code.

The potential participants of this online survey are undergraduate and postgraduate students with a background in finance.

How do I agree to participate in this research?

You agree to participate in the research by completing the Consent Form. Each participant will find a copy of the Consent form and a pen on your desk. If you have no questions and are happy to begin, please sign the consent form and return the signed form to Thang Nguyen.

Your participation in this research is voluntary (it is your choice), and whether you choose to participate will neither advantage nor disadvantage you. You can withdraw from the study at any time. If you choose to withdraw from the study, then you will be offered the choice between having any data that is identifiable as belonging to you removed or allowing it to continue to be used. However, once the findings have been produced, removal of your data may not be possible.

What will happen in this research?

The project includes a stock analysis game and a survey. Participants will need to play a trading simulation game. After the game, participants will be asked to complete a questionnaire collecting sociodemographic variables and personality variables.

What are the discomforts and risks?

The stock analysis game and the survey contain no questions creating discomfort, and there will be no personal risks.

What are the benefits?

The research will contribute to finance literature by providing new evidence on investor's cognitive capacity. As a participant, you may find the results of this research useful to you in understanding the factors that may affect your trading decisions. This would help you think about your cognitive capacity and make better financial decisions in the future.

How will my privacy be protected?

Any publications will only report the average values for all participants. Nothing that will identify an individual participant will be released.

What are the costs of participating in this research?

The stock analysis game and the survey may take you 30–40 minutes to complete.

What opportunity do I have to consider this invitation?

Potential participants are given two weeks to consider participating in this research.

Will I receive feedback on the results of this research?

All participants will be able to view a summary of their answers at the end of the experiment. A summary of findings can be viewed online after completion of the study.

What do I do if I have concerns about this research?

Any concerns regarding the nature of this project should be notified in the first instance to the Project Supervisor:

Primary Supervisor: Professor Nhut (Nick) Hoang Nguyen
`Nhut.Nguyen@aut.ac.nz` 09-921-9999 Ext. 7151

Concerns regarding the conduct of the research should be notified to the Executive Secretary of AUTEC, `ethics@aut.ac.nz`, (+649) 921 9999 ext 6038.

Whom do I contact for further information about this research?

Please keep this Information Sheet and a copy of the Consent Form for your future reference. You are also able to contact the research team as follows:

Researcher Contact Details:
Primary Researcher: Thang Nguyen. `Ryq2651@autuni.ac.nz`

Project Supervisor Contact Details:
Primary Supervisor: Professor Nhut (Nick) Hoang Nguyen
`Nhut.Nguyen@aut.ac.nz` +64 9 921 9999 Ext. 7151

Approved by the Auckland University of Technology Ethics Committee on 28 May 2024, AUTEC Reference number 24/124.

Appendix B2: Participant Information Sheet (Vietnamese)

Ngày chấp thuận thông tin: 23/05/2024

Tên đề tài:

Giới hạn khả năng xử lý thông tin của nhà đầu tư.

Lời mở đầu:

Tên tôi là Thắng Nguyễn, tôi là nghiên cứu sinh tiến sĩ Tài chính tại đại học AUT. Tôi viết thư này để mời bạn tham gia vào trò chơi phân tích cổ phiếu và khảo sát về đặc điểm cá nhân. Những người tham gia sẽ nhận được một thẻ quà tặng trị giá 50.000 VNĐ và có cơ hội nhận thêm một phiếu quà tặng trị giá 300.000 khi rút thăm ngẫu nhiên.

Mục đích của nghiên cứu này là gì?

Nghiên cứu này tìm hiểu quá trình ra quyết định của các nhà đầu tư tài chính. Nghiên cứu này quan tâm đến việc xem xét chất lượng của các quyết định tài chính bị ảnh hưởng như thế nào bởi các đặc điểm thông tin khác nhau, thời gian đưa ra quyết định và đặc điểm của một cá nhân. Tôi cũng muốn xem sự tương tác giữa các yếu tố này ảnh hưởng như thế nào đến quá trình ra quyết định và kết quả giao dịch của nhà đầu tư.

Nghiên cứu này được thực hiện để thu thập dữ liệu cho luận án tiến sĩ của tôi. Những phát hiện của nghiên cứu này có thể được sử dụng cho các ấn phẩm và thuyết trình học thuật.

Làm thế nào tôi được xác định và tại sao tôi được mời tham gia vào nghiên cứu này?

Bạn đã phản hồi tờ rơi quảng cáo nghiên cứu và quét mã QR.

Những người tham gia tiềm năng của nghiên cứu này là các chuyên gia phân tích và tư vấn có kiến thức nền tảng và kinh nghiệm về tài chính.

Làm thế nào để tôi đồng ý tham gia vào nghiên cứu này?

Bạn chấp thuận tham gia nghiên cứu này bằng cách ký vào "Đơn Đồng ý". Mỗi người tham gia sẽ tìm thấy một bản sao của đơn này và một cây bút trên bàn của bạn. Nếu bạn không có thắc mắc gì và muốn bắt đầu, vui lòng ký vào đơn và gửi lại cho Thắng Nguyễn.

Việc bạn tham gia vào nghiên cứu này là tự nguyện (đó là sự lựa chọn của bạn) và việc bạn chọn tham gia sẽ không mang lại lợi ích cũng như bất lợi cho bạn. Bạn có thể rút khỏi nghiên cứu bất cứ lúc nào. Nếu bạn chọn rút khỏi nghiên cứu thì bạn sẽ được lựa chọn giữa việc xóa bất kỳ dữ liệu nào có thể nhận dạng bạn hoặc cho phép dữ liệu đó tiếp tục được sử dụng. Tuy nhiên, một khi các kết quả đã được phân tích, việc xóa dữ liệu của bạn có thể không thực hiện được.

Điều gì sẽ xảy ra trong nghiên cứu này?

Thí nghiệm này bao gồm một trò chơi phân tích chứng khoán và một cuộc khảo sát. Người tham gia sẽ cần chơi một trò chơi mô phỏng giao dịch. Sau trò chơi, người tham gia sẽ được yêu cầu hoàn thành một bảng câu hỏi thu thập các biến số nhân khẩu học và các biến số tính cách.

Có những khó chịu và rủi ro nào trong thí nghiệm này?

Trò chơi phân tích chứng khoán và khảo sát không có câu hỏi nào gây khó chịu và sẽ không có rủi ro cá nhân.

Có những lợi ích gì từ việc tham gia thí nghiệm?

Đề tài này sẽ đóng góp vào các nghiên cứu về tài chính bằng cách cung cấp bằng chứng mới về năng lực nhận thức của nhà đầu tư. Với tư cách là người tham gia, bạn có thể thấy kết quả của nghiên cứu này hữu ích cho bạn trong việc hiểu các yếu tố có thể ảnh hưởng đến quyết định giao dịch tài chính của bạn. Điều này sẽ giúp bạn suy nghĩ về năng lực nhận thức của mình và đưa ra những quyết định tài chính tốt hơn trong tương lai.

Quyền riêng tư của tôi sẽ được bảo vệ như thế nào?

Các kết quả sẽ chỉ báo cáo giá trị trung bình của tất cả người tham gia. Không có thông tin cá nhân nào được tiết lộ.

Thời gian tham gia vào nghiên cứu này là bao nhiêu?

Tổng thời gian của trò chơi phân tích chứng khoán và khảo sát kéo dài khoảng 30–40 phút để hoàn thành.

Thời gian để tôi xem xét lời mời này?

Những người tham gia tiềm năng có hai tuần để cân nhắc việc tham gia vào nghiên cứu này.

Tôi có nhận được phản hồi về kết quả của nghiên cứu này không?

Tất cả những người tham gia sẽ có thể xem bản tóm tắt các câu trả lời của họ khi kết thúc thử nghiệm. Bản tóm tắt kết quả có thể được xem trực tuyến sau khi hoàn thành nghiên cứu.

Tôi phải làm gì nếu tôi có quan ngại về nghiên cứu này?

Bất kỳ mối quan ngại nào về nghiên cứu này phải được thông báo trước tiên cho Giám sát dự án:

Người hướng dẫn chính: Giáo sư Nhựt (Nick) Hoàng Nguyễn
`Nhut.Nguyen@aut.ac.nz` (+649) 921-9999 Ext. 7151

Những quan ngại liên quan đến việc tiến hành nghiên cứu cần được thông báo cho Thư ký điều hành của AUTEC theo email `ethics@aut.ac.nz`, hoặc số điện thoại (+649) 921 9999 ext 6038.

Tôi phải liên hệ với ai để biết thêm thông tin về nghiên cứu này?

Vui lòng giữ lại Bảng thông tin này và một bản sao của "Đơn Đồng ý" để bạn tham khảo sau này. Bạn cũng có thể liên hệ với nhóm nghiên cứu theo cách sau:

Thông tin liên hệ của nghiên cứu viên:
Nghiên cứu viên: Thắng Nguyễn (`Ryq2651@autuni.ac.nz` hoặc `thang.nguyen@aut.ac.nz`)

Thông tin liên hệ của Giám sát dự án:
Giám sát viên chính: Giáo sư Nhut (Nick) Hoang Nguyen
`Nhut.Nguyen@aut.ac.nz` +64 9 921 9999 Ext. 7151

Appendix C1: Consent Form (English)

Consent Form

Project title: ***The limit of an investor's capacity to process information***

Project Supervisor: ***Prof. Nhut (Nick) H. Nguyen***
Assoc. Prof. James Phillips
Prof. Saten Kumar

Researcher: ***Thang Nguyen***

I have read and understood the information provided about this research project in the Information Sheet dated 23/05/2024.

I have had an opportunity to ask questions and to have them answered.

I understand that taking part in this study is voluntary (my choice) and that I may withdraw from the study at any time without being disadvantaged in any way.

I agree to take part in this research.

I wish to receive a summary of the research findings (please tick one):
Yes No

Participant's signature: ....

Participant's name: ....

Participant's contact details (if appropriate):

....

....

....

....

Date: ....

Approved by the Auckland University of Technology Ethics Committee on 28 May 2024 AUTEC Reference number 24/124.

Appendix C2: Consent Form (Vietnamese)

ĐƠN ĐỒNG Ý

Tên đề tài: ***Giới hạn năng lực xử lý thông tin của nhà đầu tư***

Giáo sư hướng dẫn: ***Giáo sư Nhut (Nick) H. Nguyen***
Phó Giáo sư James Phillips
Giáo sư Saten Kumar

Người thực hiện đề tài: ***Thắng Nguyễn***

Tôi đã đọc và hiểu thông tin được cung cấp về dự án nghiên cứu này trong Bảng thông tin được chấp thuận ngày 23/05/2024.

Tôi đã có cơ hội đặt câu hỏi và nhận được câu trả lời.

Tôi hiểu rằng việc tham gia nghiên cứu này là tự nguyện (lựa chọn của tôi) và tôi có thể rút khỏi nghiên cứu bất cứ lúc nào mà không bị thiệt thòi dưới bất kỳ hình thức nào.

Tôi đồng ý tham gia vào nghiên cứu này.

Tôi mong muốn nhận được bản tóm tắt các kết quả nghiên cứu (Vui lòng đánh dấu vào ô phù hợp):
Có Không

Chữ ký của người tham gia: ....

Tên của người tham gia: ....

Thông tin liên lạc của người tham gia (nếu thích hợp):

....

....

....

....

Ngày: ....

Được phê duyệt bởi Hội Đồng Đạo đức của Đại học Công nghệ Auckland (AUT) vào ngày 28 tháng 5 năm 2024 AUTEC Số tham chiếu 24/124.

Appendix D1: Assumptions and Formulae (English)

Assumptions:

- There are no transaction costs.
- The current stock prices may not be fairly reflecting their intrinsic values, which can be estimated using the following formulas.

Price to Earnings (P/E) ratio:

$$\text{P/E ratio} = \frac{\text{Stock Price}}{\text{Earnings per share (EPS)}}$$

Gordon Growth Model (also known as the Dividend Discount Model):

$$V = \frac{D_1}{r-g} = \frac{EPS_1 \times (1-b)}{r-g} = \frac{EPS_1 \times (1-b)}{r - (\text{ROE} \times b)}$$

- V = Stock price
- D_1 = Estimated dividends for the next period
- EPS_1 = Estimated Earnings per share for the next period
- r = Required Rate of Return
- g = Growth rate of dividend
- b = Plowback ratio (dividend retention ratio)
- ROE = Return on equity

Capital Asset Pricing Model (CAPM):

$$r = R_f + \beta \times (R_m - R_f)$$

- r = Required Rate of Return
- R_f = Risk-free rate
- β = Beta of the company
- R_m = Expected market return

Appendix D2: Assumptions and Formulae (Vietnamese)

Giả thiết:

- Không có chi phí giao dịch.
- Giá cổ phiếu hiện tại trên thị trường có thể không phản ánh đúng giá trị nội tại của cổ phiếu. Chúng ta có thể tính giá trị nội tại của cổ phiếu bằng cách sử dụng các công thức dưới đây:

Chỉ số P/E (Price to Earnings):

$$\text{Chỉ số P/E} = \frac{\text{Giá cổ phiếu}}{\text{Thu nhập trên một cổ phiếu}}$$

Mô hình Gordon:

$$V = \frac{D_1}{r-g} = \frac{EPS_1 \times (1-b)}{r-g} = \frac{EPS_1 \times (1-b)}{r - (\text{ROE} \times b)}$$

- V = Giá trị nội tại của cổ phiếu
- D_1 = Cổ tức dự kiến trên một cổ phiếu trong năm tiếp theo
- EPS_1 = Thu nhập dự kiến trên một cổ phiếu trong năm tiếp theo
- r = Tỷ suất sinh lời kỳ vọng của cổ phiếu
- g = Tốc độ tăng trưởng không đổi của cổ tức
- b = Tỷ lệ tái đầu tư (plowback ratio) hay tỷ lệ thu nhập giữ lại (earnings retention ratio)
- ROE = Tỷ suất lợi nhuận trên vốn chủ sở hữu

Mô hình CAPM:

$$r = R_f + \beta \times (R_m - R_f)$$

- r = Tỷ suất sinh lời kỳ vọng của cổ phiếu
- R_f = Lãi suất phi rủi ro
- β = Hệ số beta của cổ phiếu
- R_m = Tỷ suất sinh lợi kỳ vọng của thị trường

Appendix E: Task Complexity Definition

	Level 1 (P1)	**Level 2 (P2)**	**Level 3 (P3)**	**Level 4 (P4)**
Earnings per share just updated	2.00	2.50	2.00	2.00
Company P/E ratio	9.80			
Earnings retention ratio (b)		70.00%	70.00%	68.00%
Sustainable growth rate (g)		4.00%	5.00%	
Return on equity (ROE)				7.35%
Stock required rate of return (R)		9.00%		
Stock systematic risk (β)			0.75	0.71
Risk-free rate (R_f)			4.00%	4.00%
Expected market return (R_m)			12.00%	11.00%
Current market stock price	17.64	15.00	12.00	16.00
Calculation method	1/ Calculate $P = \text{P/E} \times \text{EPS}$	1/ Calculate $D = E \times (1-b)$ 2/ Calculate $P = D/(R-g)$	1/ Calculate $R = R_f + \beta(R_m - R_f)$ 2/ Calculate $D = E \times (1-b)$ 3/ Calculate $P = D/(R-g)$	1/ Calculate $g = b \times \text{ROE}$ 2/ Calculate $R = R_f + \beta(R_m - R_f)$ 3/ Calculate $D = E \times (1-b)$ 4/ Calculate $P = D/(R-g)$
Number of cues	3	5	7	7
Number of calculation steps	1	2	3	4

Appendix F1: Demographics / Personality Questions (English)

Financial literacy questions

1. **Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?**
    - More than $102
    - Exactly $102
    - Less than $102
    - Don't know
    - Prefer not to say
2. **Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?**
    - More than today
    - Exactly the same
    - Less than today
    - Don't know
    - Prefer not to say
3. **If interest rates rise, what will typically happen to bond prices?**
    - They will rise
    - They will fall
    - They will stay the same
    - There is no relationship between bond prices and the interest rate
    - Don't know
    - Prefer not to say
4. **A 15-year mortgage typically requires higher monthly payments than a 30-year mortgage, but the total interest paid over the life of the loan will be less.**
    - True
    - False
    - Don't know
    - Prefer not to say
5. **Buying a single company's stock usually provides a safer return than a stock mutual fund.**
    - True
    - False
    - Don't know
    - Prefer not to say

Personal traits items

Trait	Item
Extraversion	Usually like to spend my free time with people Dislike being the center of attention Like going out a lot Avoid company
Agreeableness	Sympathize with others' feelings Am concerned about others Am sensitive to the needs of others Use others for my own ends
Conscientiousness	Like order Start tasks right away Work hard Neglect my duties
Neuroticism	Get overwhelmed by emotions Worry about things Panic easily Am a worrier
Openness	Am full of ideas Am able to come up with new and different ideas Am an original thinker Love to think up new ways of doing things

Demographic questions

What is your age?

- 18–24
- 25–34
- 35–44
- 45–54
- 55–64
- 65+

What is your gender?

- Male
- Female
- Non-binary/third gender
- Prefer not to say

How much of your education was devoted to finance?

- A lot
- Some

- Little
- Hardly at all
- Do not know
- Refusal

How many years have you been investing in stock markets?

- 0 years
- Less than 2 years
- 2 to 5 years
- More than 5 years

Suppose you are the only income earner in the family, and you already have a good job guaranteed to give you your current income every year for life. You are given the opportunity to take a new, equally good job. With a 50% chance it will double your income, and with a 50% chance, it will cut your income by 20%. Would you take the new job?

- Yes
- No

Suppose the chances were 50% that it would double your income and 50% that it would cut your income by 33%. Would you take the new job?

- Yes
- No

Suppose the chances were 50% that it would double your income and 50% that it would cut your income by 50%. Would you take the new job?

- Yes
- No

Appendix F2: Demographics / Personality Questions (Vietnamese)

Câu hỏi về kiến thức tài chính

1. **Giả sử bạn có $100 trong tài khoản tiết kiệm và lãi suất là 2%/năm. Sau 5 năm, bạn có bao nhiêu trong tài khoản tiết kiệm này nếu bạn không rút tiền ra khỏi tài khoản?**

    - Nhiều hơn $102
    - $102
    - Ít hơn $102
    - Không biết
    - Không muốn trả lời

2. **Giả sử lãi suất trên tài khoản tiết kiệm của bạn là 1%/năm và lạm phát là 2%/năm. Sau 1 năm, bạn có thể mua được bao nhiêu hàng hóa với số tiền trong tài khoản này?**

    - Nhiều hơn hiện tại
    - Bằng với hiện tại
    - Ít hơn hiện tại
    - Không biết
    - Không muốn trả lời

3. **Nếu lãi suất tăng, điều gì thường xảy ra với giá trái phiếu?**

    - Giá trái phiếu sẽ tăng
    - Giá trái phiếu sẽ giảm
    - Giá trái phiếu không thay đổi
    - Không có mối liên hệ giữa giá trái phiếu và lãi suất
    - Không biết
    - Không muốn trả lời

4. **Khoản vay thế chấp có thời hạn 15 năm thường yêu cầu mức thanh toán hàng tháng cao hơn khoản vay thế chấp có thời hạn 30 năm. Tuy nhiên, tổng tiền lãi phải trả trong suốt thời hạn của khoản vay 15 năm sẽ ít hơn so với khoản vay 30 năm.**

    - Đúng
    - Sai
    - Không biết
    - Không muốn trả lời

5. **Mua cổ phiếu của một công ty thường mang lại lợi nhuận an toàn hơn so với quỹ tương hỗ cổ phiếu.**

    - Đúng
    - Sai
    - Không biết

- Không muốn trả lời

Đặc điểm cá nhân

Đặc điểm	Câu hỏi
Tính hướng ngoại	Thường thích dành thời gian rảnh của tôi để giao tiếp với mọi người Không thích trở thành trung tâm của sự chú ý Thích đi ra ngoài nhiều Tránh tụ tập bạn bè
Tính dễ chịu/hòa đồng	Thông cảm với cảm xúc của người khác Quan tâm đến người khác Quan tâm đến nhu cầu của người khác Lợi dụng người khác để đạt được mục đích cá nhân
Sự tận tâm	Thích sự trật tự Bắt đầu các nhiệm vụ ngay lập tức Làm việc chăm chỉ Hay bỏ bê nhiệm vụ
Sự nhạy cảm	Dễ bị chi phối bởi cảm xúc Lo lắng về nhiều thứ Dễ hoảng loạn Hay lo lắng
Sự cởi mở	Có nhiều ý tưởng Có khả năng đưa ra những ý tưởng mới và khác biệt Có tư duy độc lập Thích tìm tòi những cách mới để làm việc

Các câu hỏi nhân khẩu học

Bạn bao nhiêu tuổi?

- 18–24
- 25–34
- 35–44
- 45–54
- 55–64
- 65+

Giới tính của bạn:

- Nam
- Nữ
- Giới tính thứ 3
- Không muốn trả lời

Bạn đã được học bao nhiêu kiến thức về tài chính?

- Rất nhiều
- Khá đáng kể
- Một ít
- Không đáng kể
- Không biết
- Không muốn trả lời

Thời gian bạn đã tham gia đầu tư vào thị trường chứng khoán là?

- Chưa bao giờ
- Ít hơn 2 năm
- 2 đến 5 năm
- Nhiều hơn 5 năm

Giả sử bạn là người có thu nhập duy nhất trong gia đình và bạn đang có một công việc tốt, đảm bảo duy trì thu nhập hiện tại cho đến lúc nghỉ hưu. Bạn được giới thiệu cơ hội nhận một công việc mới, tốt không kém công việc hiện tại. Công việc mới sẽ có thể giúp tăng gấp đôi thu nhập hiện nay của bạn (xác suất 50%), nhưng cũng có thể làm giảm 20% thu nhập hiện nay của bạn (xác suất 50%). Bạn có nhận công việc mới không?

- Có
- Không

Giả sử công việc mới có thể giúp tăng gấp đôi thu nhập hiện nay của bạn (xác suất 50%), nhưng cũng có thể làm giảm 33% thu nhập hiện nay của bạn (xác suất 50%). Bạn có nhận công việc mới không?

- Có
- Không

Giả sử công việc mới có thể giúp tăng gấp đôi thu nhập hiện nay của bạn (xác suất 50%), nhưng cũng có thể làm giảm 50% thu nhập hiện nay của bạn (xác suất 50%). Bạn có nhận công việc mới không?

- Có
- Không

Appendix G1: Qualtrics Screenshots (English)

Practice question

CONTENT	Company			
	P1	P2	P3	P4
Analysts just update expected Earnings per share to	1.50	2.50	2.37	1.85
Company P/E ratio	12			
Earnings retention ratio (b)		70%	74%	68%
Sustainable growth rate (g)		4%	5%	
Return on equity (ROE)				7.35%
Stock required rate of return (R)		9%		
Stock systematic risk (β)			0.67	0.71
Risk-free rate (Rf)			4%	4%
Expected market return (Rm)			11.50%	11%
Current stock price	16.50	15.00	15.37	16.28

Click here to see formula

What is the intrinsic value of stock of each Company? (answer to 2 decimal places)

	Company P1	Company P2	Company P3	Company P4
Intrinsic value				

Based on the intrinsic value you have calculated above, what are you going to do with stock of each Company ?

	P1	P2	P3	P4
Buy				
Hold				
Sell				

Next

Question examples

Condition 1 (2 companies/question)

CONTENT	Company	
	D1	D2
Analysts just update expected Earnings per share to	2.30	1.90
Earnings retention ratio (b)	70%	68%
Sustainable growth rate (g)	4%	
Return on equity (ROE)		7.35%
Stock required rate of return (R)	9%	
Stock systematic risk (β)		0.71
Risk-free rate (Rf)		4%
Expected market return (Rm)		11%
Current stock price	12.42	15.20

0241

Click here to see formula

Based on the above information, what do you think the stocks' intrinsic values should be? (answer to 2 decimal places)

	D1	D2
Intrinsic value		

Based on the intrinsic value you have calculated above, do you want to... the stock?

	D1	D2
Buy	○	○
Hold	○	○
Sell	○	○

Next

Condition 2 (4 companies/question)

CONTENT	Company			
	E1	E2	E3	E4
Analysts just update expected Earnings per share to	2.15	1.94	1.85	1.70
Earnings retention ratio (b)	70%	66%	68%	60%
Sustainable growth rate (g)	5%	4.5%		
Return on equity (ROE)			7.35%	10.83%
Stock systematic risk (β)	0.75	0.80	0.71	0.73
Risk-free rate (Rf)	4%	3.5%	4%	5%
Expected market return (Rm)	12%	11%	11%	12.5%
Current stock price	12.90	14.47	16.28	17.02

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Click here to see formula

Based on the above information, what do you think the stocks' intrinsic values should be? (answer to 2 decimal places)

	E1	E2	E3	E4
Intrinsic value				

Based on the intrinsic value you have calculated above, do you want to... the stock?

	E1	E2	E3	E4
Buy	○	○	○	○
Hold	○	○	○	○
Sell	○	○	○	○

Next

Condition 3 (6 companies/question)

CONTENT	Company					
	B1	B2	B3	B4	B5	B6
Analysts just update expected Earnings per share to	2.05	1.85	2.26	2.00	1.80	2.20
Company P/E ratio	9.40	8.46	7.05			
Earnings retention ratio (b)				70%	66%	74%
Sustainable growth rate (g)				5%	4.5%	5%
Stock systematic risk (β)				0.75	0.80	0.67
Risk-free rate (Rf)				4%	3.5%	4%
Expected market return (Rm)				12%	11%	11.5%
Current stock price	17.34	14.05	17.49	12.00	13.46	15.73

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Click here to see formula

Based on the above information, what do you think the stocks' intrinsic values should be? (answer to 2 decimal places)

	B1	B2	B3	B4	B5	B6
Intrinsic value						

Based on the intrinsic value you have calculated above, do you want to... the stock?

	B1	B2	B3	B4	B5	B6
Buy	○	○	○	○	○	○
Hold	○	○	○	○	○	○
Sell	○	○	○	○	○	○

Next

Mental effort measure

AUT

Please choose the best response.

	Very, very low mental effort	Very low mental effort	Low mental effort	Rather low mental effort	Neither low nor high mental effort	Rather high mental effort	High mental effort	Very high mental effort	Very, very high mental effort
How much mental effort you have invested in this task	○	○	○	○	○	○	○	○	○

Appendix G2: Qualtrics Screenshots (Vietnamese)

Practice question

Dữ liệu	Công ty			
	P1	P2	P3	P4
Các nhà phân tích vừa cập nhật thu nhập dự kiến trên một cổ phiếu trong năm tiếp theo (EPS_1)	1,50	2,50	2,37	1,85
Chỉ số P/E của công ty	12			
Tỷ lệ thu nhập giữ lại (b)		70%	74%	68%
Tốc độ tăng trưởng không đổi của cổ tức (g)		4%	5%	
Tỷ suất lợi nhuận trên vốn chủ sở hữu (ROE)				7,35%
Tỷ suất sinh lời kỳ vọng của cổ phiếu (r)		9%		
Hệ số beta của cổ phiếu (β)			0,67	0,71
Lãi suất phi rủi ro (R_f)			4%	4%
Tỷ suất sinh lời kỳ vọng của thị trường (R_m)			11,50%	11%
Giá cổ phiếu hiện tại trên thị trường	16,50	15,00	15,37	16,28

Xác định giá trị nội tại của cổ phiếu từng công ty (đáp án làm tròn đến chữ số thập phân thứ 2)

	P1	P2	P3	P4
Giá trị nội tại của cổ phiếu				

ựa trên giá trị nội tại của các cổ phiếu vừa được tính, bạn sẽ làm gì với cổ phiếu của từng công ty (Mua/Giữ/Bán)?

	P1	P2	P3	P4
Mua	○	○	○	○
Giữ	○	○	○	○
Bán	○	○	○	○

Tiếp theo

Question examples

Condition 1 (2 companies/question)

DỮ LIỆU	Công ty		Đơn vị
	E1	E2	
Các nhà phân tích vừa cập nhật thu nhập dự kiến trên một cổ phiếu trong năm tiếp theo (EPS_1)	2,15	1,85	$
Tỷ lệ thu nhập giữ lại (b)	70%	68%	
Tốc độ tăng trưởng không đổi của cổ tức (g)	5%		
Tỷ suất lợi nhuận trên vốn chủ sở hữu (ROE)		7,35%	
Hệ số Beta của cổ phiếu (β)	0,75	0,71	
Lãi suất phi rủi ro (R_f)	4%	4%	
Tỷ suất sinh lời kỳ vọng của thị trường (R_m)	12%	11%	
Giá cổ phiếu hiện tại trên thị trường	12,90	16,28	$

Xác định giá trị nội tại của cổ phiếu từng công ty (đáp án làm tròn đến chữ số thập phân thứ 2)

	E1	E2
Giá trị nội tại của cổ phiếu		

Dựa trên giá trị nội tại của các cổ phiếu vừa được tính, bạn sẽ làm gì với cổ phiếu của từng công ty (Mua/Giữ/Bán)?

	E1	E2
Mua	○	○
Giữ	○	○
Bán	○	○

Mental effort measure