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ORIGINAL RESEARCH

Experienced Well-Being and Compliance Behaviour: New Applications of Quality of Life theories, Using AI and Real-Time Data

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Abstract
The study of well-being has continued to evolve significantly over the past three decades, extending the foundational progress documented by Diener et al. (1999) through advances in measurement, cross-national surveys, and the emergence of high-frequency, real-time indicators. One of the most pressing issues in contemporary well-being research is the intersection between experienced well-being measures and societal compliance, especially in times of uncertainty. Effective crisis response depends not only on well-designed policies but also on how populations emotionally interpret uncertainty and respond behaviourally. This paper introduces a framework in which experienced well-being indicators are repositioned as behavioural inputs that shape compliance with public health interventions. Drawing on interdisciplinary theories, we argue that emotional readiness plays a critical role in driving prosocial behaviour during times of crisis. Using a macro-panel at the country–day level dataset and applying XGBoost and SHAP, we examine how dynamic, within-country features, both structural and subjective, predict compliance with COVID-19 vaccination policy. Results show that general trust and happiness are among the strongest predictors of compliance, often rivalling or exceeding traditional factors like GDP per capita or healthcare spending. Our findings show experienced well-being indicators not only predict compliance within countries but also have cross-national relevance, providing a foundation for more psychologically informed policy design. We propose that policymakers integrate these emotional indicators into crisis response systems to improve behavioural effectiveness and public cooperation.

Keywords Compliance · Global crisis · Experienced well-being · Emotions · XGBoost · SHAP

JEL classification C55 · H12 · I12 · I18 · Z13

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Introduction

A pressing issue in contemporary well-being research is the intersection between experienced well-being[1] and societal compliance during crises. This is because effective policy depends not only on design but also on emotional and behavioural readiness (Dagorn et al., 2024; Razzaq et al., 2025). Whether during a pandemic, a climate emergency, or political upheaval, compliance with collective interventions depends on more than information or enforcement. It requires individuals to feel empowered, supported, and affectively positive. Experienced well-being shapes how people interpret uncertainty, assess risk, and decide to act. Thus, fostering well-being and social cohesion is not a secondary outcome but a strategic tool for achieving widespread behavioural cooperation.

Our primary aim is to identify factors responsive to policy interventions and capable of influencing behavioural outcomes across countries. These factors must react rapidly and consistently to policy interventions, as timely action is critical to preventing or mitigating crises. Our secondary aim is to assess whether dynamic experienced well-being indicators can fulfil this role by capturing fast-moving, cross-national behavioural signals.

We propose a repositioning of experienced well-being as a behavioural input rather than merely an outcome. During crises, people face ambiguous decision contexts. In such settings, experienced well-being functions as a heuristic, guiding behaviour when information is incomplete or overwhelming. To test this, we use the COVID-19 pandemic (crisis) and include an affect balance[2] (happiness on a scale from 0 to 10 with 5 being neutral) and emotions correlated with happiness to predict compliance (collective behaviour).

Our model specification to predict compliance, although grounded in theory, is unique and differs from previous studies, which often use surveys, low-frequency or only within data, with few combining affect and emotion-based features, measured in real-time with structural within and between indicators. Additionally, our compliance measure is unique as it is a continuous, objective proxy of the decision to comply (e.g., vaccination rates as % of the eligible population), which differs from the more common approach: self-reported intention to comply.

Subsequently, we use machine learning models to achieve our aims, given their benefits compared to classic econometrics. We adopt a three-stage approach (see Section "Methodology" for details) and, in each stage, use an eXtreme Gradient Boosting (XGBoost) model to train our data to determine the most important features (factors) for complying with public health guidelines. We evaluate performance by testing the model's power to predict compliance on an unseen dataset. Furthermore, we rely on SHapley Additive exPlanations (SHAP) to explain the out-

[1] Experienced well-being (sometimes called hedonic well-being or experienced happiness) refers to the emotional quality of an individual's everyday experience—the frequency and intensity of experiences of joy, fascination, anxiety, sadness, anger, and affection that make one's life pleasant or unpleasant (Kahneman & Deaton, 2010).

[2] The happiness variable represents an affect balance, derived as the difference between positive and negative sentiment scores extracted from Twitter data, thereby capturing the net emotional tone expressed within each country-day. Please refer to Supplementary Information A for full discussion.

put of our global XGBoost model. SHAP uses concepts from cooperative game theory to assign a contribution value (or "credit") to each feature for its contribution to a specific prediction. Using SHAP absolute values will inform us about the ranking (absolute importance) of our subjective and structural variables at within- and between-country levels. Using SHAP's visualisation plots, we identify the relationships between the features and compliance, interaction (moderating effects) and threshold points (inflexion).

This paper advances the literature in several ways. First, it repositions traditional well-being theories by treating experienced well-being indicators (usually the outcome of these theories), particularly affect balance, trust and fear, as leading behavioural indicators of collective behaviour during uncertain times such as crises. By integrating these with behavioural and social theories, we offer an interdisciplinary framework that explains how experienced well-being is related to societal compliance under uncertainty. Therefore, our study makes a theoretical contribution by using experienced well-being theories as input and bridging them to collective behaviour theories. Second, by combining both subjective (measured in real-time) and structural variables, we assess the within-country dynamics of compliance and identify common predictors that can react rapidly in response to policy and positively influence behaviour across countries, contributing to the development of more universally applicable policy tools. Third, we employ innovative methods of experienced well-being measurement, including real-time sentiment data and interpretable machine learning models (XGBoost and SHAP), to determine important features, functional relationships, moderating and threshold points, for precise policy formation. These tools enhance the robustness of our analysis, offer more timely insights for policymakers, and open new avenues for crisis-responsive and psychologically informed policy design. This study contributes to emerging conversations about the role of affective science, Artificial Intelligence (AI), and behavioural theory in shaping the future of well-being research and public governance.

Our results support our theoretical repositioning of experienced well-being as input to mobilise prosocial behaviour in response to crisis and predict collective compliance with policy interventions. Furthermore, we find that real-time measures of trust, happiness, and fear are the factors that react rapidly and consistently to policy interventions across countries. These factors are therefore capable of influencing behavioural outcomes and offer actionable insights for policymakers aiming to mobilise prosocial behaviour in response to crisis interventions rapidly. Given their relevance across countries, they should be integrated into policy frameworks and preparedness guidelines as core behavioural inputs. Policymakers seeking to mitigate uncertainty or avert systemic risks must, therefore, prioritise the monitoring and enhancement of population-level experienced well-being as a strategic tool for effective intervention.

The rest of the paper is structured as follows. The next section provides our theoretical foundation, which is followed by a review of the existing literature on compliance. The section "Data and Variables" describes the data and the selected variables, while the section "Methodology" outlines the methodology used. The "Results and Interpretation" section follows, while the paper concludes in the "Conclusion" section.

Theoretical Overview

In this section, we propose our model that repositions experienced well-being not merely as outcomes of good governance but as inputs that shape collective behavioural responses under uncertainty. During crises, people face ambiguous decision contexts. In such settings, experienced well-being functions as a heuristic, guiding behaviour when information is incomplete or overwhelming.

This proposed model synthesises six theoretical perspectives:

Subjective Well-Being (SWB)

Diener's (1984) theory of SWB distinguishes between cognitive life evaluations (e.g., life satisfaction) and experienced well-being measures, such as happiness, fear and anxiety. In our study, the distinction is important as it relies on novel real-time experienced well-being measures derived from tweets and sentiment. The theory highlights experienced well-being as a key indicator of behaviour. Fredrickson's (2004) broaden-and-build theory offers a psychological mechanism through which positive experienced well-being can promote adaptive, prosocial behaviour during crises. Negative experienced well-being may either prompt precautionary action or reduce engagement, depending on the framing.

Self-Determination Theory (SDT)

According to Deci & Ryan (1985), intrinsic motivation arises when individuals feel autonomous, competent, and related. Positive, experienced well-being serves as a signal that these psychological needs are being met, making compliance more likely. Conversely, negative experienced well-being may signal coercion or helplessness, undermining motivation.

Social Capital Theory (SCT)

Social capital theory (Putnam, 1995) emphasises the importance of trust, social networks, and norms of reciprocity in fostering cooperation and compliance. In collective contexts, trust and happiness act as an affective infrastructure that reduces uncertainty, increases reciprocity, and promotes cooperation.

Mood-as-Input Theory (MIT)

Martin (2001) theorises that mood effects depend on the decision rule being applied. Under uncertainty, such as the COVID-19 pandemic, individuals may interpret positive experienced well-being as a sign that continued engagement (e.g., compliance) is warranted. In contrast, negative experienced well-being may be read as a cue to disengage unless reframed constructively.

Collective Emotion Theory (CET)

From Aminzade & McAdam (2001), we draw the insight that emotions are socially shared. Trust and fear are not only personal but also collectively held states that shape group identity and collective action. Shared happiness or institutional trust fosters a sense of "we-ness" that facilitates cooperation.

Sen's Capability Approach

We draw on the Capability Approach (Sen, 1985) to conceptually link experienced well-being and behavioural compliance. While SWB focuses on states of well-being and behavioural models on action, the Capability Approach bridges the two theories as it frames well-being not only as a state of mind, but as a function of freedom to choose a life you value, and the opportunity to act. Trust and happiness can signal perceived capability; when individuals feel empowered, socially supported, and able to act autonomously, they are more likely to comply voluntarily with collective health measures.

Collectively, these six perspectives form the theoretical foundation for our empirical framework. Each theory contributes a specific behavioural or motivational mechanism that is operationalised in our model through measurable, real-time indicators. SWB and SDT explain how affective states such as happiness and autonomy signal motivational readiness to comply. SCT and CET provide the relational dimension, linking interpersonal and institutional trust to collective cooperation. MIT specifies the cognitive process through which individuals interpret emotional cues to decide whether to persist in compliance under uncertainty. Finally, Sen's Capability Approach bridges these psychological and social mechanisms by framing well-being as both a state of mind and a capacity to act, thereby connecting emotional states to observable behaviour. In our empirical model, these theoretical elements are represented by dynamic, within-country indicators, happiness, trust (general and in government), and fear derived from real-time data. Using XGBoost and SHAP allows us to quantify and visualise how these theoretically grounded variables influence compliance across countries and over time. This integration operationalises abstract theoretical constructs into measurable behavioural inputs, thereby linking the conceptual and empirical dimensions of our study.

Therefore, our integrated model provides a new way to understand compliance, not as purely rational or structural, but as the result of affectively mediated decision-making under uncertainty.

Literature Review

In this section we review existing literature on compliance, drawing insights from past studies that investigated the COVID-19 crisis and highlighting the contributions of the current study.

Trust in Institutions and Society

Several studies highlight the role of trust in institutions and social norms in shaping compliance behaviour. Sarracino et al. (2024) examined compliance with containment policies using a time-varying measure derived from Big Data sources such as the Oxford Policy Tracker and Google mobility data. They found that compliance fluctuated over time and was positively correlated with trust in institutions and other individuals, as inferred from emotion analysis on Twitter data. Similarly, van Lissa et al. (2022) identified injunctive norms—the belief that others should comply—as the strongest predictor of self-reported compliance (outcome variable) to preventive measures. Their Random Forest analysis, based on survey data from 28 countries, indicated that descriptive norms (perceived adherence of fellow citizens) also played a crucial role in compliance. Both studies emphasise that social trust and perceived collective adherence significantly influence individuals' likelihood of following health guidelines.

Psychological and Psychosocial Predictors

The role of psychological and psychosocial factors in compliance was explored using machine learning techniques. Roma et al. (2020) utilised logistic regression, support vector machines, naïve Bayes, and random forests to predict compliance behaviour based on psychological and psychosocial variables such as self-efficacy, risk perception, civic attitudes, and personality traits. Their models achieved strong predictive performance (ROC AUC 0.82–0.91), highlighting perceived efficacy as the most critical determinant of compliance. Similarly, Pavlović et al. (2022) found that moral identity was the strongest predictor of compliance, while conspiracy beliefs and collective narcissism negatively impacted adherence. Their Random Forest analysis also revealed that cultural and pandemic-stage differences influenced compliance behaviour, with conspiracy beliefs being more detrimental in early pandemic stages and self-control becoming more influential in later stages.

Socio-Demographic and Economic Influences

Multiple studies investigated the impact of demographic and economic factors on compliance. Uddin et al. (2021) analysed survey data from Japan using Classification and Regression Tree (CART) analysis and multiple regression models. They found that women, parents, and married individuals exhibited higher compliance, whereas smokers and those with lower trust in government policies were less likely to adhere to preventive measures. Economic factors, such as income and education, showed weak effects on compliance. Similarly, Bakkeli (2023) explored socio-demographic and occupational influences in Norway using Gradient Boosting Machines (GBM), Elastic Net Regression, Support Vector Machines (SVM) and K-Nearest Neighbours (KNN) to predict self-perceived exposure risk. SHapley Additive exPlanations (SHAP) were used to determine the most influential predictors of risk perception. Their results indicated that work-life conflict and compliance with non-pharmaceutical interventions (NPIs) were the strongest predictors of perceived exposure risk, with urban residents and family households reporting higher risk perceptions.

Contextual and Behavioural Factors

The influence of contextual and behavioural factors on compliance was examined in several studies. Hajdu et al. (2022) used Random Forest models on survey data from 16 countries to analyse why individuals left their homes despite voluntary isolation guidelines. They found that fear of infection (top three predictors in 12 out of 16 countries) and social responsibility increased compliance. In contrast, feelings of being “caged” at home significantly contributed to non-compliance, with notable cultural variations (e.g., stronger impact in the UK and Slovakia, minimal impact in Japan and Greece). Furthermore, the perceived adherence of fellow citizens significantly influenced individual compliance. Monteiro (2023) also highlighted the importance of behavioural factors, finding that social interaction frequency was a key predictor of adherence, with XGBoost outperforming other machine learning models in classification accuracy and drawing on insights from SHAP. Additionally, vaccination and trust in medical institutions increased compliance. Their study emphasised country-specific variations in compliance due to policy differences and cultural norms.

Policy Implications and Trends Over time

Policy-related factors and temporal trends in compliance were explored in various studies. van Lissa et al. (2022) found that government stringency measures had a weak influence on compliance, suggesting that social norms more strongly drove voluntary adherence than enforcement. They also observed a decline in compliance over time (March-May 2020), aligning with the concept of pandemic fatigue. Bakkeli (2023) noted that by 2021, living conditions (urban vs. rural residence) had become more relevant predictors of compliance, reflecting shifts in risk perception as the pandemic evolved.

From the discussion in this section, we note that for Hajdu et al. (2022), Uddin et al. (2021), and Pavlović et al. (2022), the outcome variables were binary variables (yes/no). Bakkeli (2023) used a subjective continuous self-perceived exposure risk to COVID-19 measured across different settings, like home, work, and public places. van Lissa et al. (2022) used the level of compliance with preventive behaviours (e.g., social distancing, hand washing, a composite measure of compliance) and Monteiro (2023) used 3 and 4-point Likert scales, categorical or dichotomic variables. Sarracino et al. (2024) defined compliance as the degree of association between people’s behaviours and COVID-19 containment policies. In contrast, Roma et al. (2020) measured compliance using COVID-19 protective measures, for example, people answered questions such as “It is suggested that all persons avoid crowded places. Are you complying with this?”

Therefore, our study differs from the previous literature in that our outcome variable is proxied by the proportion of vaccinated individuals relative to those who were eligible to receive the vaccine. It is an *objective*, *continuous variable* representing a high level of variance and is not restricted to only a yes or no answer, nor does it rely on *subjective* self-reported compliance (with infection prevention behaviour), which might be biased. Additionally, our study includes subjective experienced well-being indicators measured in real-time (a novel method) and is the first to use machine learning algorithms to predict compliance. Furthermore, we reposition traditional well-being theories by treating experienced well-being indicators (usually the outcome of these theories), particularly affect balance, trust and fear, as leading behavioural indicators of collective behaviour during uncertain times such as crises.

Data and Variables

Construction of Datasets

The time period under consideration varies by country and starts from the date of the first vaccine administered. It includes all phases of the vaccine rollout, ending with the period immediately preceding the booster dose rollout. Please refer to Table B1 in Supplementary Information B. We consider the data for ten countries: seven Northern Hemisphere countries: Belgium, Germany, Great Britain, France, Italy, the Netherlands, and Spain; and three Southern Hemisphere countries: Australia, New Zealand and South Africa, to find a retrospective view of those factors that mattered most for compliance.

We use a merged dataset, including the Google COVID-19 Open Data[3], the World Health Organisation, the World Bank and the United Nations data (see Supplementary Information C) for the structural variables and our three time-series datasets derived from tweets[4]. The three Twitter datasets reflect (i) happiness levels and emotions of countries, (ii) emotions towards government policy (i.e., the vaccine) and (iii) emotions towards government institutions.

The selection of data sources followed two main criteria: frequency and comparability. To measure happiness and emotions, we included only data sources that provide high-frequency observations (daily or weekly) to allow the detection of short-term behavioural and emotional dynamics over time. Low-frequency surveys, such as annual well-being or trust datasets, were excluded because they cannot capture temporal variation in compliance. In addition, to measure structural variables, we selected cross-nationally comparable and publicly available datasets with transparent collection methodologies, ensuring consistency across countries and over the full observation period. This approach allowed us to merge subjective and objective indicators while preserving both temporal sensitivity and international comparability.

The following section briefly explains the Twitter data, with a more detailed explanation available in Supplementary Information A. Tweets are extracted in real-time based on a geographic bounding box corresponding to the country in question. Next, we use sentiment and emotion analysis to score the tweets. We aggregate the scores and derive indices for happiness and each of the eight emotions. For the Twitter data-

[3] Available from https://health.google.com/covid-19/open-data/explorer.

[4] Available from https://gnh.today/.

sets related to the government and COVID-19 vaccines, we used specific keywords to identify only those tweets directly related to the topic.

To derive the dataset related to the COVID-19 vaccines, we extracted tweets using the keywords: *vaccinate*, *vacc*, *vaccine*, *Sputnik V*, *Sputnik*, *Sinopharm*, *Astrazeneca*, *Pfizer (if NEAR) vaccine*, *Pfizer-BioNTech*, *Johnson & Johnson*, and *Moderna*.

For the dataset related to governments, we extracted tweets using the keywords: *government*, *parliament*, *ministry*, *minister*, *senator*, *MPs*, *legislator*, *political*, *politics*, *prime minister.*

After extraction, we analysed the text of the tweets to determine whether the extracted tweets related to vaccines and the government indeed did captured these concepts. We found that less than 3% of tweets did not directly fit into the themes; therefore, the "noise" captured in the extracted tweets related to the specific topics is minimal.

Target/Outcome Variable

Our outcome variable is compliance, which we proxy as those individuals who actively chose to get vaccinated when they became eligible for the vaccine (before the booster shot was introduced).

Therefore, we calculate our compliance measure as vaccinated individuals as a percentage of the population eligible to receive the vaccine (Eq. 1). This continuous outcome variable offers advantages over binary or categorical measures (e.g., "yes-no" responses or Likert scales), as it captures more granular variation in compliance rates across countries, which increases behavioural insights. For a breakdown of eligible populations through each vaccination rollout phase per country, see Table B2 in Supplementary Information B.

$$Compliance = \frac{Cumulative\ vaccinated\ population}{Eligible\ population} \tag{1}$$

The eligible population differed from country to country, but what is important to remember is that people generally had the freedom to choose whether or not to get vaccinated, regardless of the vaccination policy in place.

The reader should note that our proxy for compliance will differ from official country statistics on the percentage of vaccinated individuals during the time period under consideration, since countries did not take the population eligible to receive the vaccine into consideration as we do.

Predictor Variables/Features

The selection of our features from the various datasets is well-grounded in theory (Section "Theoretical Overview") and existing literature (Section "Literature Review"). The features distinguish between two key dimensions of quality-of-life: the type of variable (subjective vs. structural) and the level at which it operates; within-country (dynamic) vs. between-country (fixed). Please refer to Table 1.

This dual classification is essential for both theoretical clarity and policy application. Structural variables are external and objective and capture either within-country or

Table 1 Two dimensions: subjective vs. structural and within-country vs. between-country

Category	Within-Country Effect	Between-Country Effect
Subjective Indicators	Daily variations in trust (general and in the government), fear of vaccines, and happiness derived from tweets explain daily individual behaviour within countries.	*(Not modelled)* — Theoretically, subjective averages per annum can explain cross-country differences over a longer time period. In the current study, the time analysed is less than a year; thus, the subjective behavioural variables are constant and do not contribute to addressing the research questions.
Structural Features	Dynamic within effects - the availability of local health support	Fixed between-country effects - Structural country characteristics such as GDP per capita, national health infrastructure, and population density explain cross-country differences

See Table C1, Supplementary Information C, for a detailed breakdown of the 16 features included in the models

between-country variations. Meanwhile, subjective measures, such as happiness and trust, which change daily, capture dynamic behavioural responses within countries.

While cross-national differences in average levels of subjective measures, such as happiness or trust, certainly exist, they do not meaningfully inform our analytical focus. These national averages are calculated per annum, and our time period of analysis is less than one year; therefore, a constant number, which does not reflect any behavioural responsiveness. In contrast, our framework conceptualises dynamic experienced well-being as a real-time behavioural signal that fluctuates within countries in response to policy interventions and evolving crisis conditions. Including slow-moving national averages would therefore conflate structural background differences with the short-term emotional dynamics that are central to our study. Excluding between-country subjective indicators maintains both theoretical coherence and empirical precision, ensuring that our results reflect policy-relevant dynamic experienced well-being changes rather than static national traits. This dual approach allows us to interpret SHAP-derived feature importance not only in terms of which features are most important but also in terms of policy-level needs.

To clean our data sets, we started by identifying missing data. If feature values were missing at random and constituted less than 3% of the observations, we imputed the missing value using the mean, mode, or interpolation using surrounding values, depending on the nature of the data. Variables with substantial missingness (e.g., international support and emergency health investment, with over 65% missing) were dropped from the dataset to preserve data integrity.

We then addressed multicollinearity by selecting the most appropriate representative variable among highly correlated ones, for example, choosing between newly confirmed cases and newly tested cases, based on stability and predictive contribution. These steps ensured that our dataset was both lean and predictive.

Table 2 shows the descriptive statistics and highlights the dual classification of features as explained in Table 1. From Table 2, we note that the mean for both trust variables is close to 5 (neutral), with values below 5 indicating negative trust. The trust features have moderate variation (std. dev. varies between 0.38 and 0.42). The mean happiness levels are relatively high, with a mean of 7.16 (happiness varies between 0 – not happy at all – 5 neutral to 10 very happy). Fear of vaccines also has a mean close to 5 with a moderate variation of standard deviation = 0.34. The variance in the experienced well-being reveals meaningful daily-level effects within countries.

As expected, the within-country structural features change over time within each country, showing high to moderate variation and include policy and time-varying health (new deceased cases) indicators. Moving to the between-country structural features, these variables do not vary within countries, especially considering the time frame of a little more than one year. However, they vary considerably between countries. We note high levels of variation in rural populations and GDP per capita.

The outcome variable, compliance, has a mean of 0.54, indicating that, on average, just over half of the eligible population complied. The standard deviation of 0.367 (1.5 times the mean) reflects substantial variability across observations over

Table 2 Descriptive statistics for the 16 features and compliance (the original values - before standardisation)

Variable	Mean	Std. dev.	Min	Max
Within-country subjective measures				
Happiness	7.16	0.42	4.63	8.55
Trust	5.20	0.38	3.33	5.38
Trust Gov	5.31	0.38	3.62	5.66
Fear Vac	5.19	0.34	3.92	5.56
Within-country structural variables				
New deceased cases as % of the population	0.00237	0.00284	0.00000	0.01950
Stringency index	60.88	16.66	22.22	96.30
Face coverings	2.89	0.79	2.00	4.00
International travel controls	2.92	0.73	1.00	4.00
Income support	1.62	0.61	0.00	2.00
Between-country structural variables				
Population rural	676820.30	1769300.00	18091.00	7641564.00
GDP per capita (US$)	39769.16	12814.63	6001.00	54907.00
Diabetes prevalence as % of the population	0.00023	0.00026	0.00006	0.00129
Population density	204.70	154.88	3.32	504.00
Females as % of the population	0.51	0.004	0.502	0.516
Nurses per 1000	9.80	4.60	1.31	19.46
Health expenditure (USD)	3759.39	1359.06	499.24	5331.82
Outcome variable				
Compliance	0.54	0.367	0.00	1.14

Source: Authors' own calculations

time. The range spans from 0.00 (no compliance) to 1.14, suggesting that in some cases, compliance exceeded 100% of the initially estimated eligible population. The high level of compliance is possibly due to over-reporting, data inaccuracies, or the inclusion of broader groups than initially defined. However, we chose to retain all observations to preserve the integrity of the original data. This wide variation over time makes compliance a suitable outcome variable for examining both within-country daily dynamics and between-country structural differences.

Methodology

XGBoost

We implement a machine learning pipeline using the XGBoost algorithm, a highly efficient, scalable gradient boosting method that constructs an additive ensemble of decision trees. Each successive tree is trained to correct the prediction errors made by the previous trees, enabling the model to capture complex, non-linear interactions between input features and compliance behaviour. XGBoost has demonstrated greater accuracy than other methods. For example, Abdurrahim et al. (2020), comparing the accuracy of different predictive modelling algorithms, show that XGBoost shows the highest accuracy score compared to other methods such as logistic regression, naïve Bayes classifier, Decision Trees, and Random Forest. Compared to classical statistical methods, XGBoost supports a more flexible and robust treatment of high-dimensional, noisy, and multicollinear data, making it ideal for our diverse, real-time dataset. Furthermore, it includes regularisation (L1 and L2) to prevent overfitting.

Our XGBoost model is defined in Eq. (2) as:

$$F_M\left(x\right) = F_0 + v\beta_{\,1} T_1\left(x\right) + v\beta_{\,2} T_2\left(x\right) + \cdots + v\beta_{\,M} T_M\left(x\right) \tag{2}$$

Where M is the number of iterations. The gradient boosting model is a weighted $(B_1 \ldots \beta_{\,M})$ linear combination of simple models $(T_1 \ldots T_M)$. $F_M\left(x\right)$ is the compliance measure as described in Section "Target/Outcome Variable".

During training, XGBoost assigns gain scores to each feature, measuring the improvement in prediction accuracy attributable to that feature. These scores allow us to determine which features the model prioritises, though they do not offer insights into effect, direction or consistency. To ensure a robust and interpretable analysis, we implement the modelling in three sequential stages as part of an integrated analysis pipeline:

- Stage 1 – Within-country models: We train separate XGBoost models for each of the ten countries to determine the most important features for compliance within national contexts. This establishes whether certain features are consistently important across countries and validates the reliability of the selected predictors.
- Stage 2 – Pooled model with country feature: We combine all country datasets and introduce a 'country' feature to assess the importance of unobserved country-level heterogeneity on compliance. Based on the result of the analysis, we determine whether features have universal applicability or are country-specific.

- Stage 3 – Global model without country feature: Finally, we pool all countries again but remove the 'country' variable to isolate universal predictors of compliance. This approach ensures that the universally essential features we identify are not merely spurious results caused by unobserved country heterogeneity or due to the average effects of features.

For each model, performance is evaluated on unseen (test) data using regression-based fit metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Square Error (RMSE). These metrics validate the model's predictive power and generalisation capacity. A good model should show similar performance across both training and test sets, with smaller test metrics (smaller errors) indicating better performance.

To test the robustness of our trained model, we vary the random splits between the training and test datasets, assessing whether the model's performance and variable importance rankings remain consistent. We further implement 5-fold cross-validation to enhance generalisability. We selected a 5-fold cross-validation scheme as a balance between bias reduction and variance control, following evidence that higher folds or repeated cross-validation offer minimal gains in accuracy estimation while increasing computational cost (Vanwinckelen & Blockeel, 2012). Additionally, we perform feature ablation tests by selectively removing input features to evaluate the stability of feature importance rankings.

SHAP Values

To interpret model outputs and provide transparency, we apply SHAP (SHapley Additive exPlanations), which decomposes each prediction into additive contributions from each feature using cooperative game theory principles (Lundberg & Lee, 2017). SHAP values are computed using the TreeExplainer, which is optimised for tree-based models like XGBoost (Lundberg et al., 2018). Additionally, we use SHAP's KernelExplainer for robustness checks in cases where feature interactions were complex.

SHAP values are computed at the observation level and quantify both the magnitude and direction of each feature's effect on the predicted outcome, while also accounting for interactions between features. For global interpretation, we calculate the mean absolute SHAP value, which allows us to rank features by importance independent of directionality. This enables us to identify features with consistently strong influence on compliance, assess whether their effects are positive or negative, detect non-linear effects and threshold points and uncover interactions (moderating effects) between features.

Specifically, we visualise model interpretation through:

1. SHAP summary plots, to compare the overall importance of features,
2. SHAP boxplots, to examine the direction and distribution of SHAP values by feature,
3. SHAP dependence plots, to explore the type of functional relationships between the outcome and the features and the plausible threshold,
4. Stratified SHAP dependence plots, to investigate moderation, such as whether levels of trust in government condition the effect of general trust.

Together, this multi-layered pipeline provides a comprehensive understanding of how both structural and dynamic subjective variables influence compliance at the country and global level.

Interpreting Feature Importance: XGBoost vs. SHAP

While XGBoost gain scores provide a useful summary of which features the model relies on during tree construction, they do not indicate whether those features increase or decrease compliance, nor whether their effect is consistent across different observations. Gain scores can also be biased toward features with more potential split points or greater cardinality.

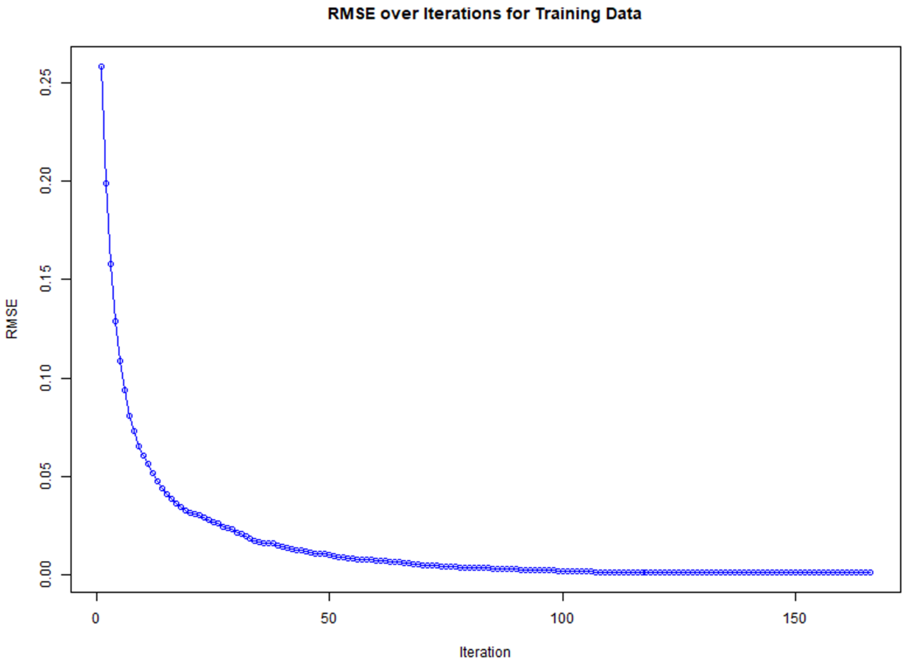
To complement this, SHAP offers a post-hoc model-agnostic, game-theoretic method to understand feature influence. Unlike XGBoost gain scores, SHAP values quantify the marginal contribution of each feature to each individual prediction while holding other variables constant. This allows us to capture both the direction and the strength of each feature's effect across different observations. In our analysis, XGBoost gain scores help identify which features the model used most frequently during training and how much they improved accuracy (global importance). Conversely, SHAP values explain how and why those features influence predictions, revealing both magnitude and direction, including interaction effects. Therefore, these two approaches provide complementary insights.

Results and Interpretations

This section presents the results of our machine learning pipeline, which integrates XGBoost and SHAP. We begin by explaining how we train a model and evaluate the overall model performance to predict the outcome variable. This is done to familiarise the reader with the process we follow throughout the paper when training models. The example we use in Section "Model Performance and Fit" is that of our final model, of which the output of the model is discussed in Section "Stage 3: XGBoost Model On Universal Feature Importance".

Model Performance and Fit

We want to remind the reader that all hyperparameter tuning was conducted exclusively on the training data using 5-fold cross-validation to optimise model parameters and ensure generalisability. Therefore, for our final XGBoost model (Section "Stage 3: XGBoost Model On Universal Feature Importance"), we first used the default settings of the XGBoost algorithm on the training data and refined the parameters to find the best fit. We started by refining the depth of the trees and tested depths between three and ten, finding three to result in the lowest root mean square error (RMSE). We set the number of iterations to 200, with a termination clause added (early stop) to stop the algorithm if the RMSE does not decrease after five iterations. After completing the refining stage, the model reached the lowest RMSE after 150 iterations (Fig. 1), ensuring we selected the most effective parameters for our analysis.



Source: Authors' own calculations.

Fig. 1 RMSE over iterations for XGBoost

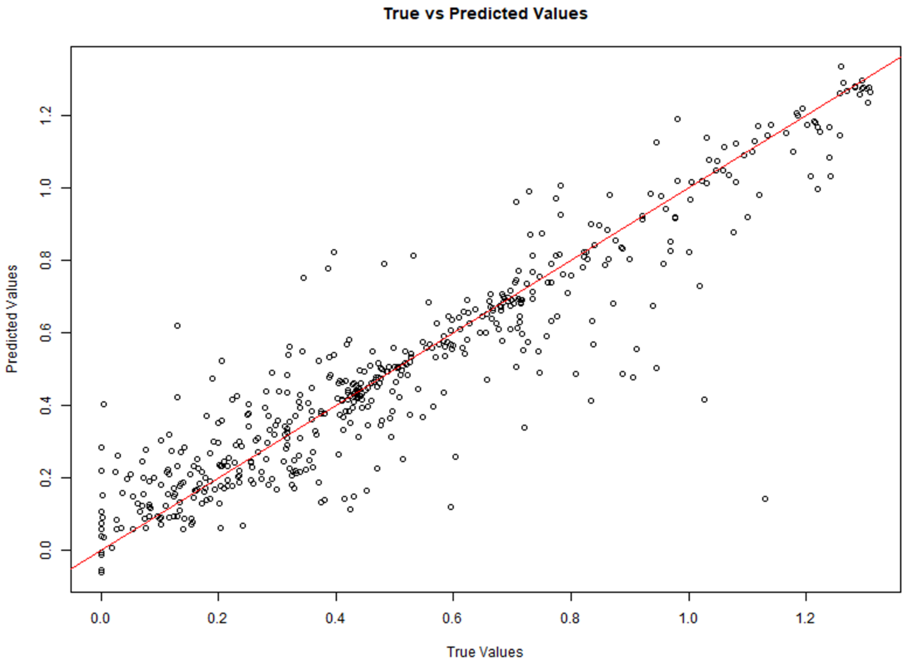
Next, we turn to the fit metrics for our XGBoost model, explaining how well our model predicts the outcome variable (compliance) based on the unseen test dataset. We notice that all measures of fit reveal small errors, indicating a good-fitting model. The metrics are: MSE is 0.026, the MAE is 0.104, and the RMSE is 0.161 (R-squared 0.782).

The scatter plot in Fig. 2 plots the “predicted” compliance scores against the “true” compliance scores of the training dataset. The red diagonal line represents perfect predictions, where the predicted value equals the true value. Most data points lie close to the red line, which indicates that the model’s predictions closely match the actual values. Furthermore, there is a reasonably symmetric spread around the diagonal line, suggesting that the model does not systematically overpredict or underpredict across the range of compliance values. The plot supports the fit metrics and is proof that the model generalises well to unseen data.

Now that we’ve illustrated our model’s ability to predict compliance, we turn to the results from the within-country analysis, highlighting those features ranking consistently as top predictors.

Stage 1: Individual Country Feature Importance

After executing the XGBoost models per country, we find that from the 16 features included in the model, similar features are consistently ranked as the most important



Source: Authors' own calculations.

Fig. 2 XGBoost: predicted compliance values plotted against the true values

features predicting compliance per country. Table 3 shows the features most often ranked in the top 5. For example, the stringency index appeared in the top 5 in all 10 countries. Similar new deceased appeared in the top 5 in 9 of the countries.

Ranking the most important based on the frequency in the top 5 rankings, we find that all are related to within-country variables. The two top-ranking features are structural within-country variables related to public health measures and the intensity of the disease. For example, the stringency index appeared ten times and the "new deceased cases" nine times in the top five most important rankings (see Table 3). The within-country subjective indicators follow these, with happiness appearing eight times and trust seven times in the top five rankings. Please see Table D1 in Supplementary Information D for country-specific results.

Within countries, similar features consistently ranked as most important, validating that these features are universally important, with an emphasis on subjective mea-

Table 3 Top 6 features among the top 5 rankings across the ten countries

Feature	Top 5 Count	Rank
Stringency index	10	1
New deceased cases	9	2
Happiness	8	3
Trust	7	4
Fear Vac	5	5
Trust Gov	4	6

Source: Authors' own calculations

sures. It is important to note that features such as GDP per capita, the rural area (sq/km), and population density, which are rather measures used in “between-country” comparisons, do not appear in the within-country importance ranking.

Stage 2: Role of the Country Feature

Stage 2 included a “country” feature (nominal variable) to establish whether country differences drive compliance. The “country” feature, therefore, helps in the training of the model to learn country-specific patterns in compliance.

If we find that the “country” feature (among all our included features) is ranked as important for compliance, it will imply that country-specific features (unobserved heterogeneity) drive compliance and that no universal policy recommendation can be made. Therefore, policy should only be country-specific. If, however, we find that unobserved country characteristics do not drive compliance, we can confidently present our final model, which determines the drivers of compliance globally.

From Supplementary Information D, Table D2, we note that the “country” feature is very low on the importance list. Therefore, we assume that the unobserved heterogeneities across countries, such as culture and norms or political systems, are already captured in observable between-country variables such as rural area and population density.

Stage 3: XGBoost Model on Universal Feature Importance

Table 4 shows the results from our XGBoost model, ranking the most important features to predict compliance (refer to Section "Model Performance and Fit" for model fit and performance evaluation). We remind the reader that the higher the “gain”, the more important the feature is in predicting compliance, in our case, defined as getting vaccinated when eligible. For example, the new deceased cases as % of the population is ranked first, and trust is the highest subjective indicator, ranked fourth. As explained in Section "SHAP Values", the most important features defined by the XGBoost model also appear as top-ranked in the mean absolute SHAP values (see Fig. 3 in Section "Magnitude of Global Feature Importance"). Therefore, we discuss the order of feature importance based on the absolute SHAP values in the next section to avoid repetition.

We also include robustness checks to test if the ranking of important features remains stable across different data splits and ablation tests (refer to Supplementary Information D, Tables D3 and D4). We consider the model robust in ranking the feature importance. Therefore, we continue with our results using SHAP values.

Stage 3: SHAP Analysis of the Global Model

Magnitude of Global Feature Importance

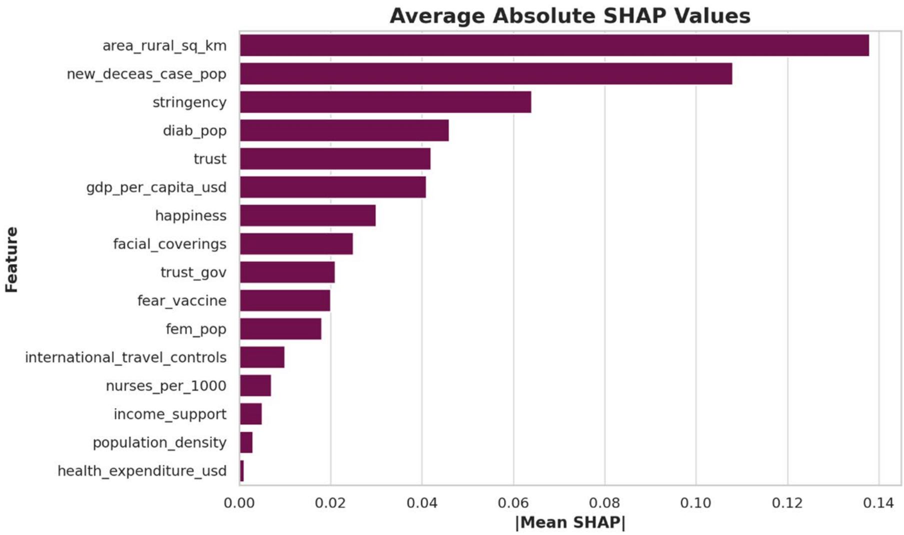
Here, we consider the features’ average absolute SHAP values, showing each feature’s marginal contribution in explaining compliance, irrespective of direction.

Table 4 Results on the order of the importance of the variables predicting compliance during times of crisis

Ranking	Feature	Importance (Gain)
1	New deceased cases as % of the population	0.3037705
2	Stringency index	0.2164748
3	Rural area (sq/km)	0.1592149
4	**Trust**	**0.0603308**
5	Diabetics as % of the population	0.0530109
6	GDP per capita ($US)	0.0709887
7	**Happiness**	**0.0550082**
8	**Trust in the government**	**0.0221293**
9	**Fear of the vaccine**	**0.0189397**
10	Facial coverings	0.0180191
11	International travel controls	0.0089626
12	Nurses per 1000 people	0.0000845
13	Females as % of the population	0.0002292
14	Income support	0.0033488
15	Population density	0.0094646
16	Health expenditure ($US)	0.0000234

Source: Authors' own calculations

Figure 3 shows that the most important feature is the between-country feature, rural area (sq/km). Other structural between-country features in the top ten are diabetes population (4) and GDP per capita (6). We realise these are important for compliance and markedly differ between countries. This is important information that needs to be considered in international compliance guidelines, as it makes countries unique.



Source: Authors' own calculations.

Fig. 3 Magnitude of feature importance (Average absolute SHAP values)

However, we aim to find dynamic variables that rapidly respond to policy and apply to all countries.

Furthermore, the following within-country structural variables are identified as part of the top ten (in order of importance): new deceased cases (2), stringency index (3), and wearing a facial cover (8). While these features play an important role in predicting compliance, and they are dynamic within countries, they are related to the outcome of the pandemic (new deceased cases) and policy measures to restrict the spread of the disease (stringency index and facial covers). Therefore, not a single one of these indicators is a dynamic behavioural measure that can rapidly affect compliance.

Features that do fulfil the necessary requirements of being responsive to policy interventions and capable of rapidly influencing behavioural outcomes in the top ten are: general trust (5), happiness (7), trust in the government (9) and fear of vaccines (10). The reader will note that these features are all subjective indicators. Therefore, if we address these features, we can achieve a rapid response to mobilise prosocial behaviour in response to crisis interventions.

We therefore have successfully achieved the study's aims of identifying factors that respond to introduced policy interventions and are capable of influencing behavioural outcomes. We have determined that dynamic experienced well-being indicators can fulfil this role by capturing fast-moving, cross-national behavioural signals. We now know "which" indicators matter the most and must now address the "how" to increase the accuracy of our policy recommendations.

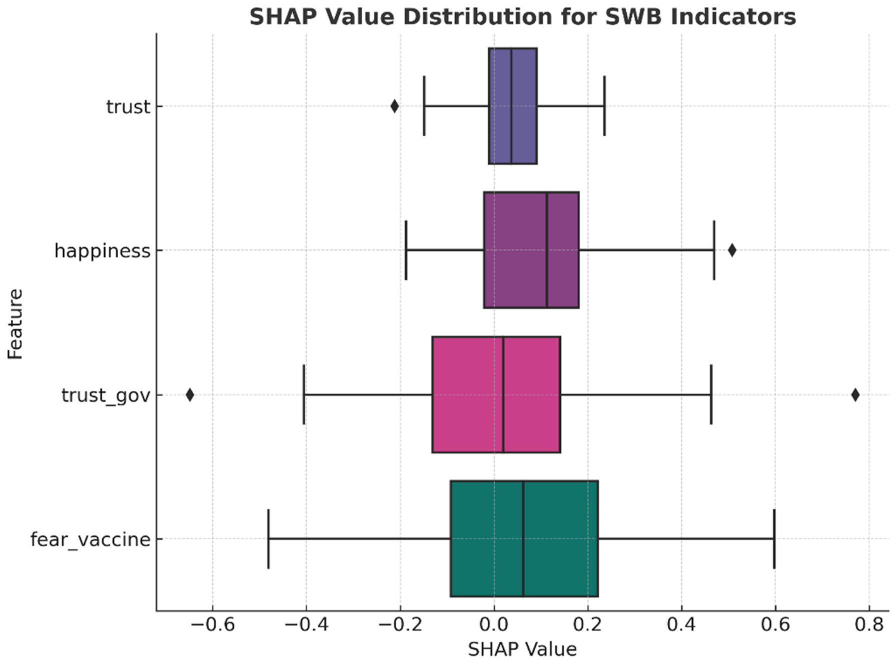
Directional Effects and Non-Linearities

Figure 4 adds directional insights into the relationship between compliance and our features. Although the spread of all features is interesting, we will focus on the dynamic within-country subjective well-being features identified in Section "Magnitude of Global Feature Importance".

From Fig. 4, we see that the SHAP values of trust are slightly right-leaning, which implies that trust in general is positively related to compliance, although we also observe negative values. This is expected as the scale ranges from distrust to trust. The spread is relatively narrow and clustered around 0, showing a stable effect across observations, and the outliers are limited; thus, most countries behave consistently.

The SHAP values for happiness are clearly right-leaning. The spread is moderately clustered around zero, with a positive median and a few outliers on both sides. From the spread of values, it seems that more SHAP values are positive, and it appears that higher happiness is related to a higher level of compliance.

We note that, similar to general trust and happiness, trust in government is slightly right-leaning with a median above zero. The spread is relatively narrower and varies by country and over time. The values are both positive and negative, likely referring to the scale of trust variables from negative to positive trust. There are several outliers, which suggest extreme distrust or surges in confidence in specific countries. To increase our grasp on the relationship between trust and compliance, we need to continue our investigation (dependency plots).



Source: Authors' own calculations.

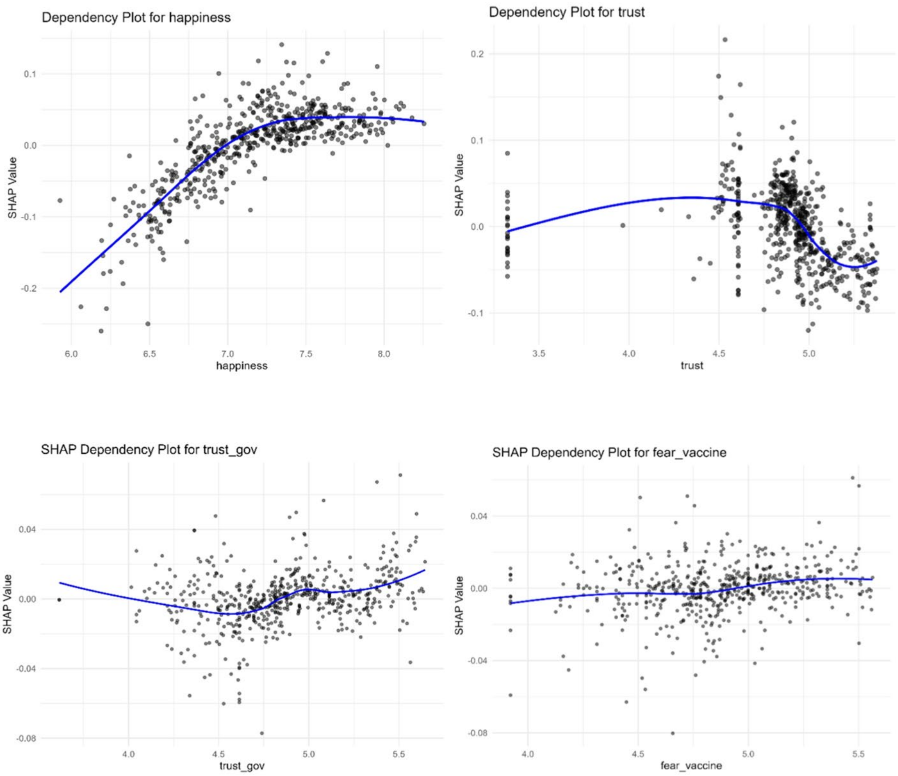
Fig. 4 Directional insight of important subjective well-being features (SHAP boxplot)

Lastly, SHAP values for fear of vaccines are slightly left-leaning, and the spread is wider than that of the other variables, which could plausibly indicate polarisation. There are many outliers to both the right and the left. The right shows that fear might be driving cautious compliance, whereas to the left, fear might reflect mistrust and non-compliance.

Considering the spread of the features, the relationships are most likely non-linear. Therefore, in the next step, we explore the learned functional form between these features of interest and compliance. For these purposes, we consider SHAP dependency plots (including LOESS lines[5]) in Fig. 5, which shows visual approximations of the functional forms learned by the model for input features and highlights the inflexion points. This knowledge gives us the appropriate tools to create effective and accurate policy recommendations.

Considering trust (top right corner), the X-axis represents levels of general trust (with values below 5 classified as low levels of trust and values above 5 as high levels of trust). At the same time, the Y-axis reflects the SHAP values of trust, which measure the marginal contribution of trust to the model's compliance predictions. The relationship is non-linear, and the functional form reveals three distinct behavioural phases. Phase 1: low trust (trust < 4.5). SHAP values increase with rising trust,

[5] LOESS stands for locally estimated scatterplot smoothing and is one of many non-parametric regression techniques, but arguably the most flexible.



Source: Authors' own calculations.

Fig. 5 SHAP dependence plots illustrating non-linear and threshold effects

indicating that marginal increases in trust among individuals enhance predicted compliance. This suggests that people who distrust others may require social reassurance to engage in collective behaviours like compliance. Phase 2: moderate trust (trust around 5.0). The SHAP value is at its highest at the transition phase between low and moderate levels of trust. The inflexion point reflects the maximum marginal influence of trust on compliance. Therefore, if trust is clustered around 5, it will be most responsive to a policy that encourages compliance. Phase 3: high levels of trust (> 5.5). Beyond the threshold of moderate trust, SHAP values (marginal contribution) of trust decline and eventually become negative. This pattern reflects the principle of diminishing marginal returns, suggesting a saturation point beyond which additional increases in trust no longer increase predicted compliance. In other words, while moderate trust levels foster acceptance and cooperative behaviour, extremely low trust undermines compliance, and excessively high trust may reflect complacency, diminishing the policy's effectiveness. Thus, optimal policy acceptance occurs at moderate levels of trust, where trust and engagement are balanced. Considering these results, we expect that there are certain moderation effects which we will investigate in Section "Interaction Effects (Moderation)".

Happiness (top left corner) has on its X-axis the happiness levels (with 0 not happy, 5 neutral, >5 happy to very happy), and on its Y-axis the SHAP value for happiness. The LOESS line illustrates the smoothed functional form of the relationship. The plot shows a non-linear relationship between happiness and its marginal contribution to compliance predictions, with clear evidence of diminishing returns at higher happiness levels.

At low levels of happiness (happiness<6.5), SHAP values are negative and increase steadily as happiness rises, indicating that less happy individuals are less likely to comply. As happiness increases from low to moderate levels, the marginal effect on compliance becomes strongly positive. Around the threshold region between 6.5 and 7.0, SHAP values cross from negative to positive, marking the inflexion point after which additional happiness yields smaller incremental gains in predicted compliance. In other words, consistent with the principle of diminishing marginal utility, once individuals reach high levels of happiness (happiness>7.0), further increases contribute little additional benefit to compliance predictions.

For policy purposes, if people have lower levels of compliance, boosting their happiness can increase compliance, but only to a certain point, i.e., whereafter the value of increased happiness diminishes.

Trust in the government (bottom left corner) shows that negative trust in the government (<5.0) has SHAP values that are mostly negative, reaching their lowest around 4.5–4.6. This indicates that distrust in government decreases the marginal contribution of trust to the compliance prediction. Neutral trust in the government (=5.0) is near the inflexion point, and SHAP values begin to rise, indicating a transition from negative to neutral effect. Positive trust (>5.0) reveals SHAP values that are increasingly positive; thus, the marginal contribution of trust in the government continues to increase with higher levels. This suggests that positive trust in government supports compliance predictions.

For policy relevance, distrust in government is a key barrier to compliance. While positive trust helps, its marginal effect increases, which suggests that restoring trust in sceptical populations is important as well as pushing already-trusting individuals to higher levels of trust.

Fear of vaccines (bottom right corner) shows that with low to moderate fear (<5.0), SHAP values are near zero or slightly negative. Therefore, the marginal contribution of low levels of fear is limited. At the transition point of 5.0, the LOESS curve turns upward. This is an inflexion point, and past this point, the marginal contribution of fear in predicting compliance increases. High fear (>5.0) has SHAP values that become slightly positive, suggesting that stronger fear may motivate some people to comply. This can be a response to risk perception, i.e., fear triggers protective behaviour like following rules. However, we believe that a moderating effect is taking place; therefore, we will investigate the moderating role of trust in the government on fear of vaccines.

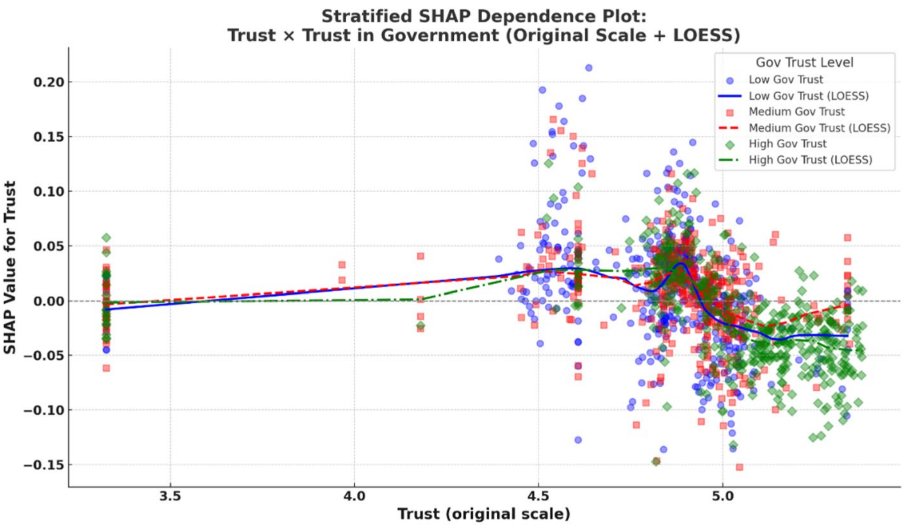
Interaction Effects (Moderation)

While SHAP values help us understand the independent effects of features, many behavioural drivers do not operate in isolation. This section explores key interactions using stratified SHAP dependence plots, which reveal how the influence of one variable changes depending on the level of another. In behavioural terms, these interaction effects point to conditional dynamics. These plots are necessary to identify nuanced patterns that standard main-effect analyses might overlook.

Figure 6 shows the SHAP dependence plot of generalised trust, stratified by levels of trust in government. On the X-axis are trust levels (original scale), and on the Y-axis are the SHAP values for trust. Trust in the government is the moderator, i.e., low, medium or high levels. When there are low levels of trust in government (blue), we see a clear upward trend in the LOESS line. As interpersonal trust increases, its positive effect on compliance strengthens, especially when trust in government is low. When there are medium levels of trust in government (red), we also see a generally positive association, but less steep than the low trust group. This implies that moderate institutional trust dampens the influence of personal trust slightly. For levels of high trust in the government (green), the LOESS line flattens or dips as general trust increases. This suggests a diminishing or even negative marginal effect of interpersonal trust on compliance in high institutional trust contexts.

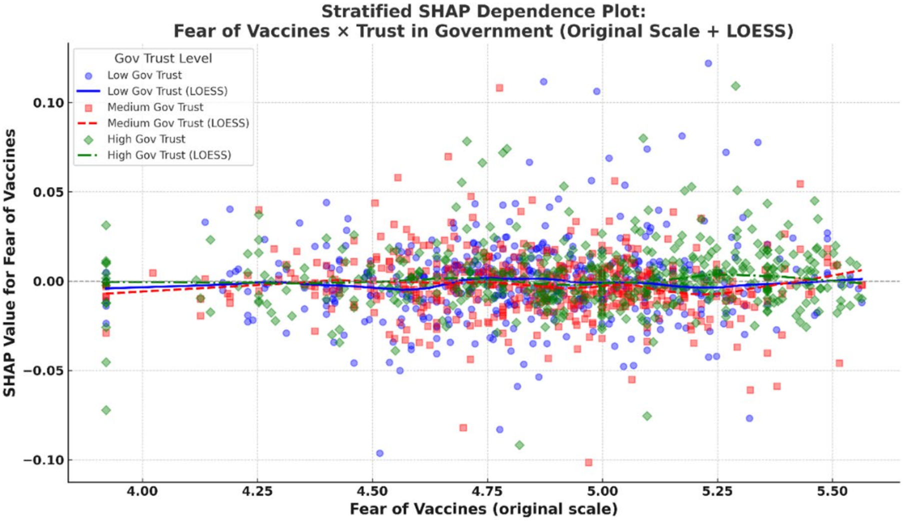
The above suggests that when people do not trust the government, their trust in others plays a stronger role in compliance, indicating that societal trust can compensate for weak confidence in government. However, when government trust is high, general trust becomes less influential, possibly due to reliance on institutions over peer networks.

Figure 7 shows the SHAP dependence plot of fear of the vaccine stratified by levels of trust in government. On the X-axis is fear of the vaccine (original scale; higher = more fear), and on the Y-axis is the SHAP values for fear of the vaccine, measuring the marginal effect on predicted compliance. We see that for levels of low



Source: Authors' own calculations.

Fig. 6 Interaction between general trust and trust in government



Source: Authors' own calculations.

Fig. 7 Interaction between trust in government and fear of the vaccine

government trust (blue), it signals that when people fear vaccines and distrust the government, they are the least likely to comply. For medium levels of trust in the government (red), the LOESS line starts near zero, dips as fear increases, then slightly recovers. This indicates a moderate negative effect of fear on compliance, suggesting the relationship is non-linear. Trust somewhat buffers the fear, but not consistently. With high levels of trust, SHAP values are less negative overall, and the curve flattens. This suggests that when people highly trust the government, fear of the vaccine has less impact on their compliance behaviour.

The above suggests that the marginal contribution of fear of vaccines has a consistently negative relationship to compliance, but the magnitude and sensitivity of this impact depend on trust in the government. Therefore, trust in the government moderates the relationship; the more people trust the government, the less damaging fear is for compliance outcomes.

Synthesis

Our results reveal the importance of experienced well-being predictors. Specifically, the subjective within-country indicators, trust, happiness, and fear, emerged as factors that can react rapidly and consistently to policy interventions across countries.

The results also support previous findings on the importance of structural features, such as rurality, mortality rates, and policy stringency, in explaining compliance patterns across countries. However, these variables are largely fixed in the short term. They provide context but lack the agility needed during fast-moving crises. As such, while they are foundational, they are insufficient for timely behavioural intervention.

We found that all the subjective well-being indicators are non-linearly related to compliance, revealing an optimal range for policy to take effect. For general trust levels, to affect behaviour and compliance, without moderation effects, it should approximate the neutral range around 5 (below 5 is very low levels of trust and above 5 is trust). General trust is also moderated by trust in the government; therefore, we find that higher trust levels increase compliance. When people do not trust the government, their trust in others plays a stronger role in the marginal contributions to compliance and vice versa. Trust in the government should consistently be at levels higher than 5, thus in the positive trust range, to encourage compliance. In terms of happiness, we found that higher levels increase compliance, but when happiness levels are already high (>7), diminishing marginal returns set in. Considering the fear of vaccines, we once again established the importance of trusting the government. We find that fear of vaccines only undermines compliance when trust in government is low. When trust in government is high, the harmful effects of fear are neutralised.

Therefore, we argue that experienced well-being indicators should be treated not merely as indicators of social mood but as strategic policy levers. By targeting modifiable, within-country emotional dynamics, policymakers can increase the behavioural readiness of populations and foster more widespread, voluntary compliance with health measures. In a crisis, structural change is too slow, but rapid subjective change is possible, measurable, and powerful.

In terms of policy implications, we maintain that it is essential to implement real-time measures of experienced well-being to foster collective compliance effectively. Understanding current emotional states allows policymakers to assess the immediate impact of interventions, whether they are successful, ineffective, or counterproductive, and adjust strategies accordingly. Alongside this, a suite of policy actions should be employed. These include positive messaging, mental health support, and promoting transparency, accountability, and anti-corruption. Daily briefings featuring verified, science-based information can help build trust, while social listening enables governments to respond swiftly to emerging concerns through policy updates or myth-busting efforts. Live Q&A sessions with health officials, pop-up vaccine clinics, and training respected local figures to explain and advocate for policies are vital for community engagement. Leveraging peer networks, such as churches and sports clubs, to share success stories enhances outreach. Furthermore, short-term economic relief measures should be implemented with high visibility, and proactive vaccine information support should be maintained to counter misinformation and boost public confidence.

Conclusions

The study of well-being has evolved through successive waves of theoretical and empirical development. The foundational progress documented by Diener et al. (1999), tracing advances from the 1960 s to the 1990 s, laid the groundwork for the contemporary phase of research. We note that in the 1990 s and early 2000 s, subjective well-being was largely assessed through large-scale surveys, focusing on relationships between economic conditions and happiness. Foundational work, such as that by Diener (1994), refined our understanding of well-being into cognitive and emotional components, while studies by Blanchflower & Oswald (1995) revealed the social and economic determinants of life satisfaction.

By the 2010 s, the emergence of Big Data and digital tools enabled researchers to capture real-time indicators of emotional well-being. Studies such as Kahneman & Deaton (2010) underscored the importance of distinguishing between life evaluation and emotional experiences, while sentiment analysis from platforms like Twitter, Facebook (Dodds et al., 2011; Iacus et al., 2015; Schwartz et al., 2016; Greyling & Rossouw, 2019) and search engine data from Google Trends (Foa et al., 2022; Ford et al., 2018; Algan et al., 2019; Murtin & Salomon-Ermel, 2024; Greyling & Rossouw, 2025) began offering real-time proxies for mental health, subjective well-being and happiness. These tools laid the groundwork for a new generation of well-being research that could react as fast as the world changed.

In a similar vein as Diener et al. (1999) reflected on the three decades spanning 1960–1990, we reflected on the last three decades and as we move further into the 21 st century, it is clear (also from this study) that machine learning and AI are playing an increasingly prominent role in predicting well-being trends and identifying areas of concern before they escalate. The transition from traditional surveys to Big Data-driven approaches, as used in this research, has provided more granular, real-time insights, enabling governments and organisations to develop targeted interventions and policies. However, the shift also raises ethical concerns regarding data privacy, consent, algorithmic bias, and the digital divide, which must be addressed to ensure equitable application of these technologies. Nonetheless, the integration of Big Data and AI with subjective well-being research continues to shape the future of well-being measurement, offering more responsive and actionable insights in an era of rapid social and economic change.

Our study extended these technological capabilities by applying machine learning to extract data and examine behavioural compliance during a time of crisis (the COVID-19 pandemic) across ten countries. We identified those factors that would react rapidly and consistently to policy interventions across countries, as timely action is critical to preventing or mitigating crises.

Our results provide compelling evidence that experienced well-being is not merely a downstream outcome of good governance but functions as a behavioural input that actively shapes collective decision-making under uncertainty. This empirically validates our conceptual model proposed in Section "Theoretical Overview". In particular, real-time subjective indicators, general trust, happiness, trust in government, and fear of vaccines were found to be among the most policy-responsive and important features. These subjective states are highly reactive to targeted, real-time policy interventions, making them powerful levers for shaping collective action in contexts marked by uncertainty.

Furthermore, our SHAP analysis revealed complex non-linear relationships and interaction effects. Notably, moderate levels of trust and higher levels of happiness were found to be important features in enhancing compliance, while excessive levels showed diminishing returns. Trust in government softened the negative effects of fear and moderated the effect of general trust, which impeded compliance, suggesting that emotional states interact in shaping behavioural outcomes. These insights reinforce the role of affective indicators as powerful tools for understanding collective behaviour.

In the future, these findings suggest a paradigm shift in how public policy could leverage emotional indicators. In a world increasingly shaped by uncertainty, from pandemics to climate crises, governments must develop emotionally intelligent policy frameworks. These should prioritise emotional readiness and trust-building alongside structural preparedness. Real-time monitoring of societal mood can serve as both an early warning system and a lever for behavioural change. The integration of subjective well-being data into policy design is not just a theoretical advance but a practical imperative.

While our study focused on developed countries, future research should extend this framework to include developing contexts where emotional, structural, and cultural dynamics may differ. As machine learning and Big Data analytics continue to evolve, so too will the capacity for real-time, nuanced, and actionable insights into the emotional foundations of societal behaviour.

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Author contributions The authors contributed equally to the manuscript. Therefore, they are joint first authors, and the displayed order of these authors alternates with each subsequent study.

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Declarations

Competing interests Talita Greyling is the editor of Pioneers in Quality of Life Theory and Research for Applied Research in Quality of Life.

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