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**Experienced well-being and compliance behaviour: new applications of Quality of Life theories,
using AI and real-time data.**

Stephanié Rossouw¹, Talita Greyling²

Abstract The study of well-being has evolved significantly over the past three decades, reflecting both theoretical advancements and real-world applications across diverse populations, domains, and times. 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 cross-national 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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1. Introduction

A pressing issue in contemporary well-being research is the intersection between experienced well-being and societal compliance during crises. This is because effective policy depends not only on design but also on emotional and behavioural readiness. 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 (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 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 5 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 output 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 inputs 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. Section 2 provides our theoretical foundation, while section 3 reviews existing literature on compliance. Section 4 describes the data and the selected variables, while section 5 outlines the methodology. The results and discussion follow in section 6, while the paper concludes in section 7.

2. 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:

2.1 *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.

2.2 *Self-Determination Theory*

According to Deci and 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.

2.3 *Social Capital Theory*

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 affective infrastructure that reduce uncertainty, increase reciprocity, and promote cooperation.

2.4 *Mood-as-Input Theory*

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.

2.5 *Collective Emotion Theory*

From Aminzade and 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.

2.6 *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.

Therefore, our model posits that experienced well-being functions as an informational and motivational input in decisions about collective action. In uncertain contexts, such as pandemics, experienced well-being shapes the perceived viability and desirability of compliance. People are more likely to comply when they feel autonomous, socially bonded, affectively positive, and empowered. Experienced well-being is, therefore, not epiphenomenal but central to collective behavioural readiness and policy responsiveness.

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.

3. Literature review

Section 3 reviews existing literature on compliance, drawing insights from past studies that investigated the COVID-19 crisis and highlighting the contributions of the current study.

3.1 *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.

3.2 *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.

3.3 *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.

3.4 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.

3.5 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 sections 3.1-3.5, we note that 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. Furthermore, 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.

4. Data and Variables

4.1 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 1. 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.

Table 1: Time period under consideration per country.

Country	Start Date	End Date
Australia	21/02/2021	7/11/2021
Belgium	5/01/2021	11/07/2021
Germany	26/12/2020	31/08/2021
Spain	27/12/2020	23/09/2021
France	27/12/2020	12/09/2021
Great Britain	8/12/2020	15/09/2021
Italy	27/12/2020	19/09/2021
The Netherlands	6/01/2021	17/11/2021
New Zealand	20/02/2021	16/01/2022
South Africa	17/02/2021	31/10/2021

We use a merged dataset, including the Google COVID-19 Open Data³, 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 tweets⁴. The three Twitter datasets reflect

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

⁴ Available from <https://gnh.today/>

i) happiness levels and emotions of countries, ii) emotions towards government policy (i.e., the vaccine) and iii) emotions towards government institutions.

This 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 datasets related to the government and COVID-19 vaccines, we used specific keywords to identify 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 the level of noise captured. Subsequently, we found that the noise was minimal in both instances.

4.2 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 (equation 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 Supplementary Information B.

$$Compliance = \frac{Cumulative\ vaccinated\ population}{Eligible\ population} \quad (1)$$

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.

4.3 Predictor variables/features

The selection of our features from the various datasets is well-grounded in theory (section 2) and existing literature (section 3). 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 2.

Table 2. 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.	<i>(Not modelled)</i> — Theoretically, subjective averages can explain cross-country differences, though these have been excluded from our model specification.
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.

This dual classification is essential for both theoretical clarity and policy application. Structural variables are external and objective and capture either within-country or between-country variations. Meanwhile, subjective measures, such as happiness and trust, which change daily, capture dynamic behavioural responses within countries. The mean national levels of subjective indicators could

theoretically also explain between-country differences, but as they are averaged over time and contribute little to explaining compliance behaviour, we exclude them from our analysis.

Furthermore, within-country effects capture daily variances in features (structural or subjective well-being), while between-country effects reflect how differences in national averages or structures (e.g., GDP per capita or population density) explain variations in outcomes across countries. 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 3 shows the descriptive statistics and highlights the dual classification of features as explained in Table 2. From Table 3, 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.

Table 3. 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.

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 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.

5. Methodology

5.1 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 equation (2) as:

$$F_M(x) = F_0 + v\beta_1 T_1(x) + v\beta_2 T_2(x) + \dots + v\beta_M T_M(x) \quad (2)$$

Where M is the number of iterations. The gradient boosting model is a weighted ($\beta_1 \dots \beta_M$) linear combination of simple models ($T_1 \dots T_M$). $F_M(x)$ is the compliance measure as described in section 4.2.

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 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. Additionally, we perform feature ablation tests by selectively removing input features to evaluate the stability of feature importance rankings.

5.2 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.

5.2.1 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.

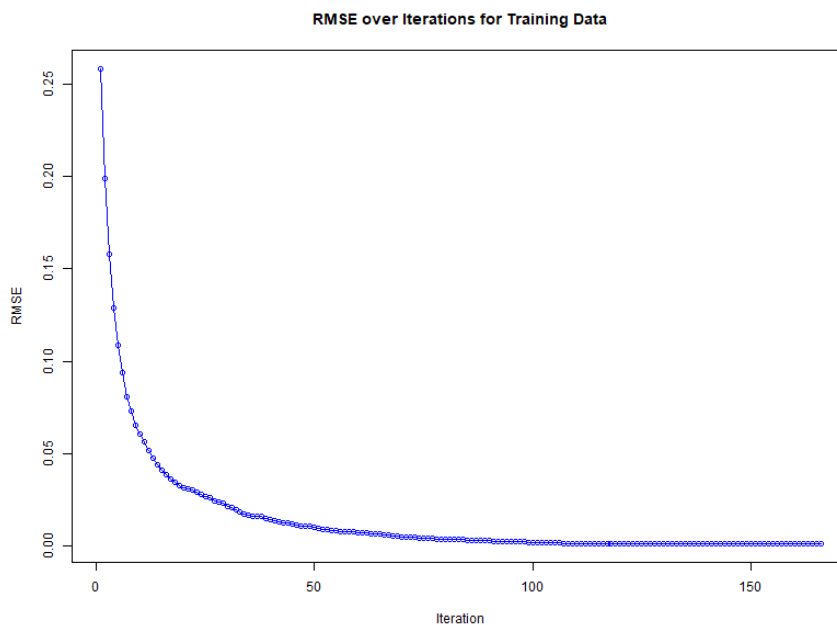
6. Results and interpretations

This section presents the results of our machine learning pipeline, which integrates XGBoost and SHAP (section 5.1). 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

which we follow throughout the paper when training models. The example we use in section 6.1 is that of our final model, of which the output of the model is discussed in section 6.4.

6.1 Model Performance and Fit

For our final XGBoost model (section 6.4), 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 (Figure 1), ensuring we selected the most effective parameters for our analysis.



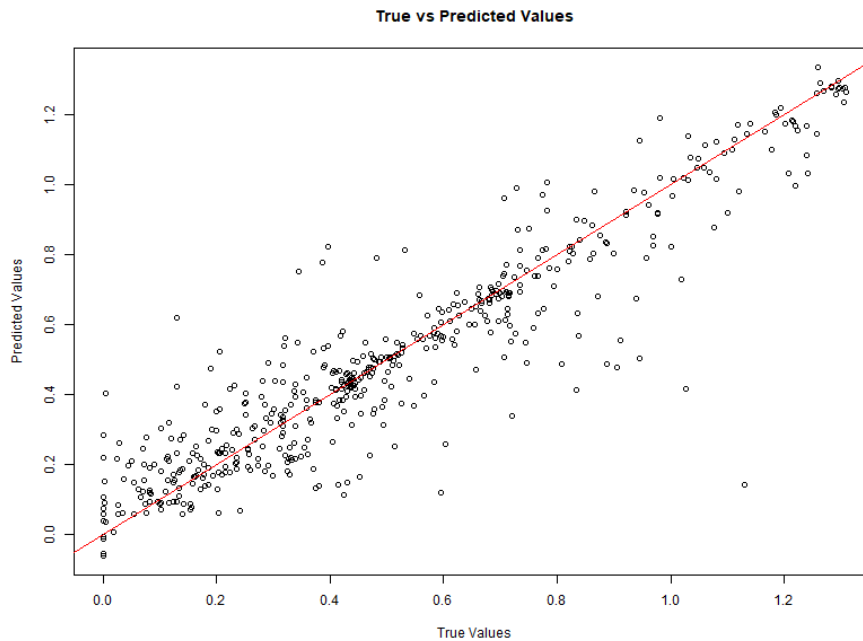
Source: Authors' own calculations.

Figure 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 Figure 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.



Source: Authors' own calculations.

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

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.

6.2 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 features predicting compliance per country. Table 4 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. The within-country subjective indicators follow these. This emphasises the importance of subjective measures for countries to address compliance. Please see Table D1 in Supplementary Information D for country-specific results.

Table 4. 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	9	3
Trust	7	4
Fear Vac	5	5
Trust Gov	4	6

Source: Authors' own calculations.

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

6.3 Stage 2: Role of the Country Feature

Stage 2 consisted of including a "country" feature (nominal or string 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.

6.4 Stage 3: XGBoost model on universal feature importance

Table 5 shows the results from our XGBoost model, ranking the most important features to predict compliance (refer to section 6.1 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 5.2, results from XGBoost models often overlap with absolute SHAP values; therefore, we discuss the order of feature importance in the next section to avoid repetition.

Table 5. 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

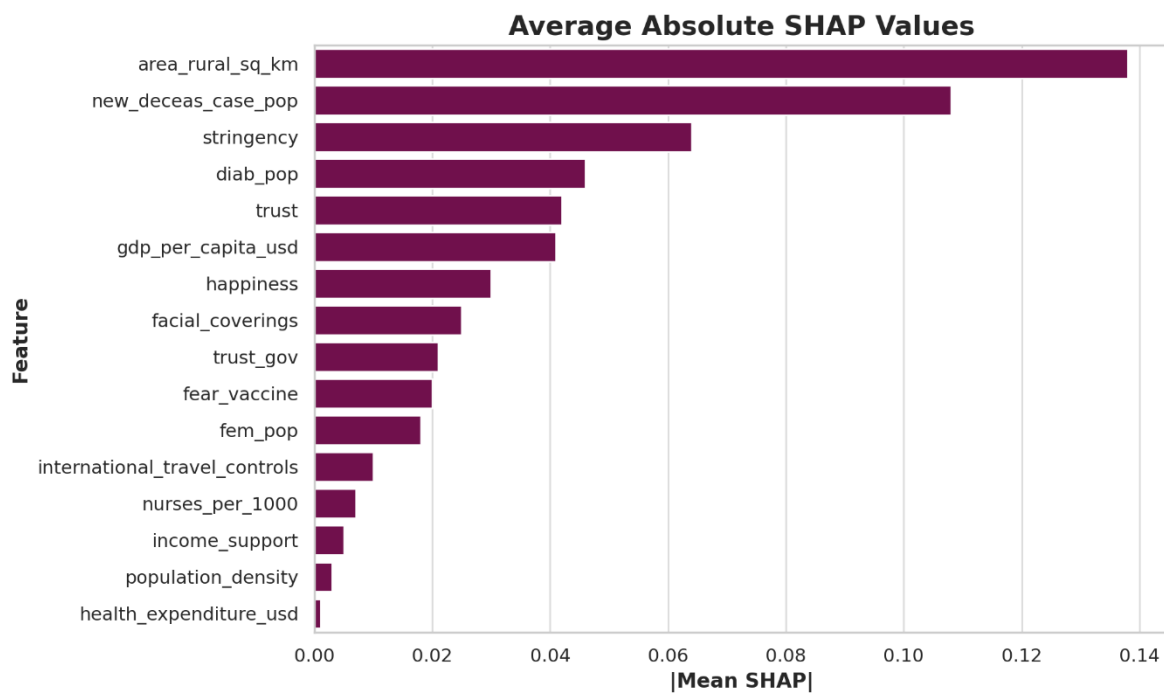
Source: Authors' own calculations.

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.

6.5 Stage 3: SHAP analysis of global model

6.5.1 Magnitude of global feature importance

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



Source: Authors' own calculations.

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

From Figure 3, we note 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. However, we aim to find dynamic variables that rapidly respond to policy and are applicable within 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

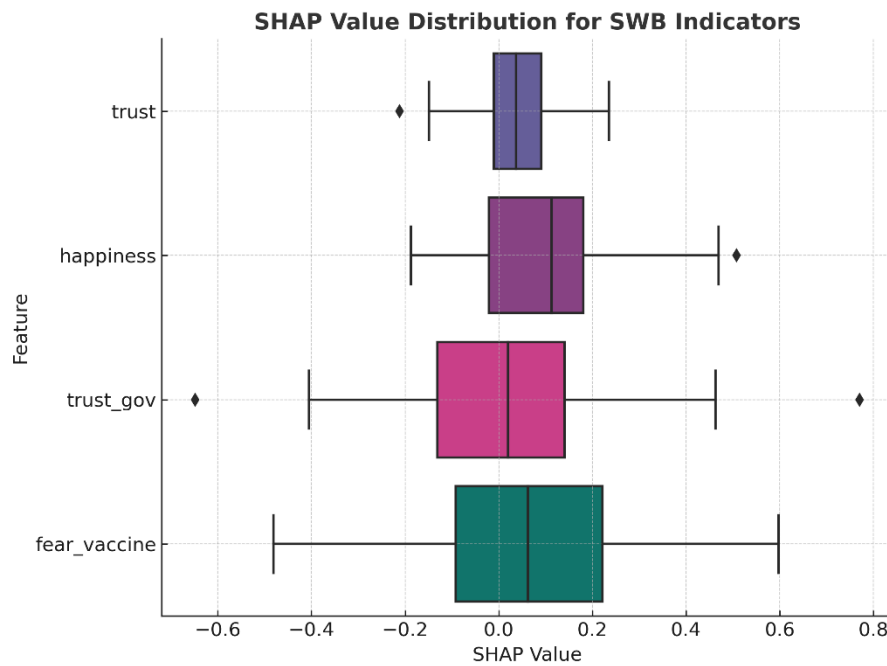
to restrict the spread of the disease (stringency index and facial covers). Therefore, not a single one of these indicators is a dynamic, policy-relevant feature that can rapidly affect behavioural changes to affect compliance.

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 are responsive to policy interventions and capable of influencing behavioural outcomes, and 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 and must now address the "how" to increase the accuracy of our policy recommendations.

6.5.2 *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 6.5.1.



Source: Authors' own calculations.

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

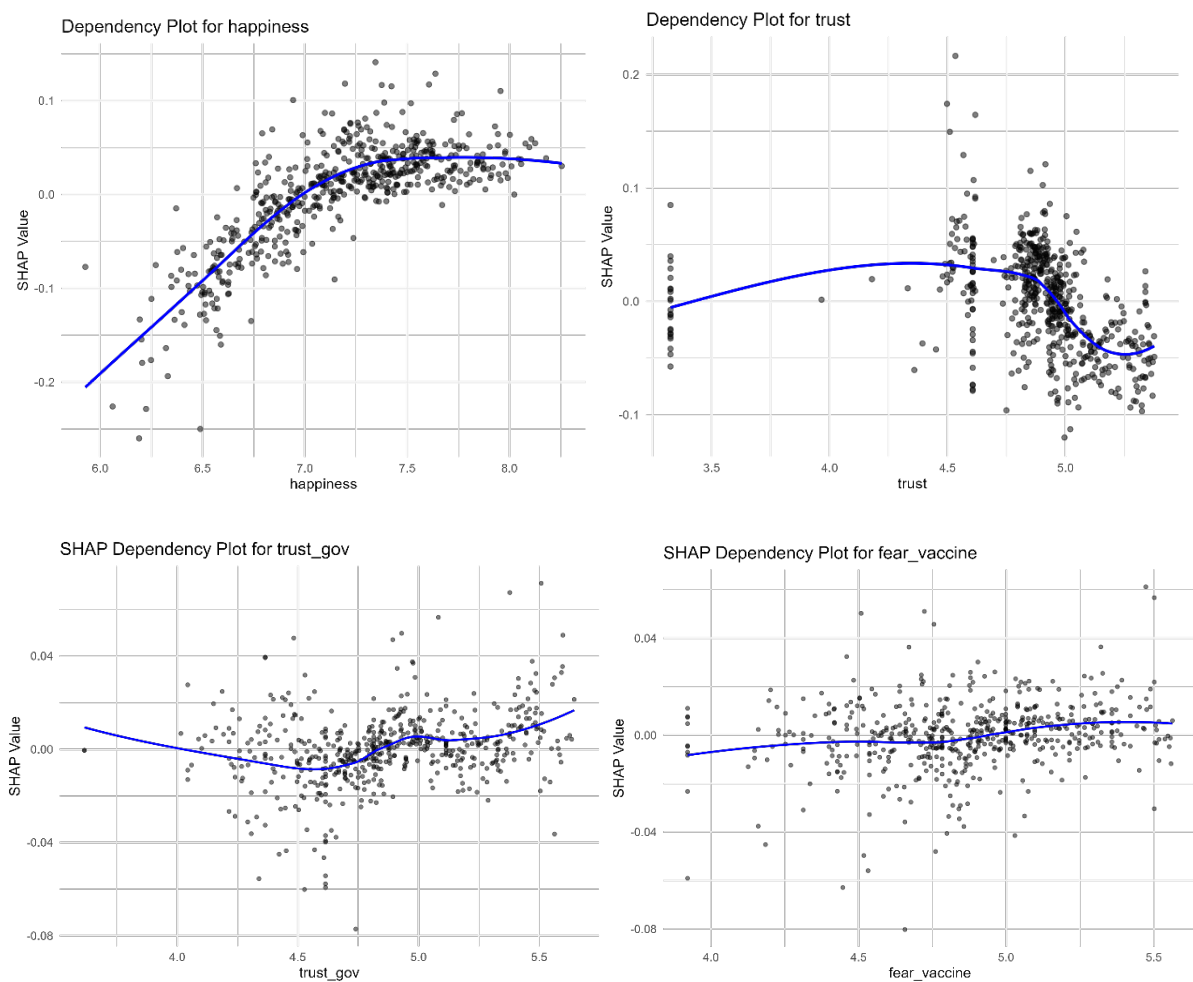
From Figure 4, we see that the SHAP values of trust are slightly right-leaning, which implies that trust in general is positively related to compliance, although we also observe negative values. This is expected as the scale ranges from distrust to trust. The spread is relatively narrow and clustered 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 seems 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).

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 that all the features have extreme values (outliers), it likely implies non-linear or interaction effects. 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 lines⁵) in Figure 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.



Source: Authors' own calculations.

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

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

Considering trust (top right corner), the X-axis represents levels of general trust (with values below 5 classified as distrust and values above 5 as trust). At the same time, the Y-axis reflects SHAP values, measuring the marginal effect of trust on the model's compliance predictions. The shape of 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, indicating that marginal increases in trust among distrustful individuals enhance predicted compliance. This suggests that people who generally 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 distrust and 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 trust (> 5.0). Beyond the threshold of moderate trust, SHAP values decline and eventually become negative. This indicates that individuals with high levels of generalised trust may be less likely to comply, possibly due to optimistic assumptions about others' behaviour ("others will do the right thing") or diffusion of responsibility.

For optimal policy, trust should be at moderate levels. Extremely low levels might reduce compliance, and extremely high levels could reduce vigilance and personal responsibility.

Considering these results, we expect that there are certain moderation effects which we will investigate next.

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, while the LOESS line indicates the smoothed functional form. This plot reveals a non-linear, upward-sloping relationship between happiness and compliance predictions. The functional form suggests diminishing returns at higher levels of happiness. Low happiness (happiness < 6.5) SHAP values are negative and increase steadily with increasing happiness. This suggests that less happy individuals are less likely to comply. As happiness increases from low to moderate, the marginal effect on compliance is strongly positive. The threshold region is between 6.5 and 7.0, and the SHAP values cross from negative to positive. This inflexion point shows that once people reach moderate happiness, their predicted compliance becomes more positive. At high happiness levels (happiness > 7.0), the curve flattens, and SHAP values remain slightly above 0. Therefore, additional happiness contributes little to higher levels of compliance. Happier individuals are generally more compliant, but once a person is moderately happy, further increases in happiness do not add much predictive power to compliance.

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.

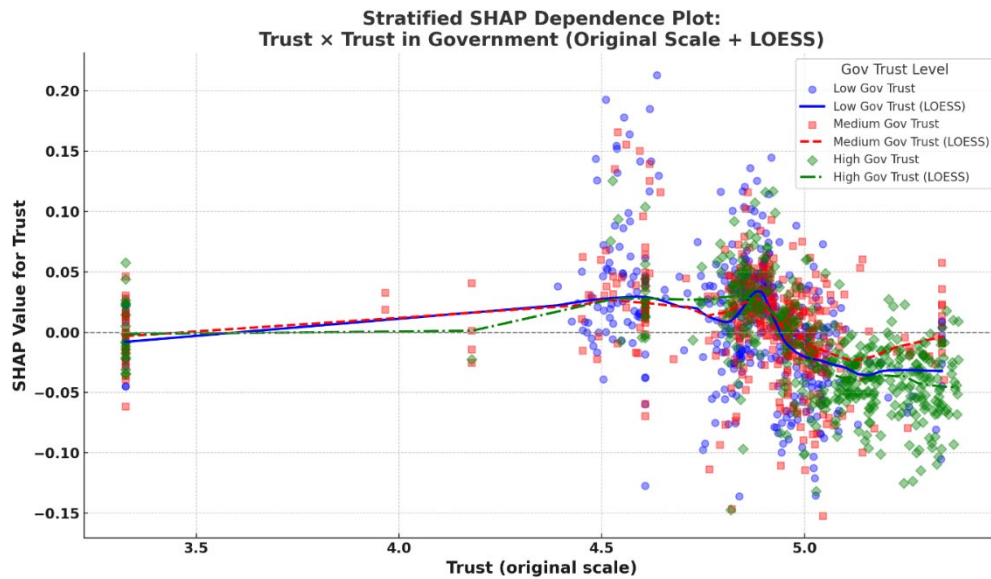
Trust in the government (bottom left corner) shows that negative trust in the government (< 5.0) has SHAP values that are mostly negative, reaching their lowest around 4.5–4.6. This indicates that distrust in government consistently reduces compliance. Neutral trust in the government ($= 5.0$) is near 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. This suggests that positive trust in government supports compliance.

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, low fear has minimal impact or is slightly negatively related to compliance. At the transition point of 5.0, the LOESS curve turns upward. This is an inflexion point, and past this point, fear's impact on compliance begins to change. 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.

6.5.3 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.

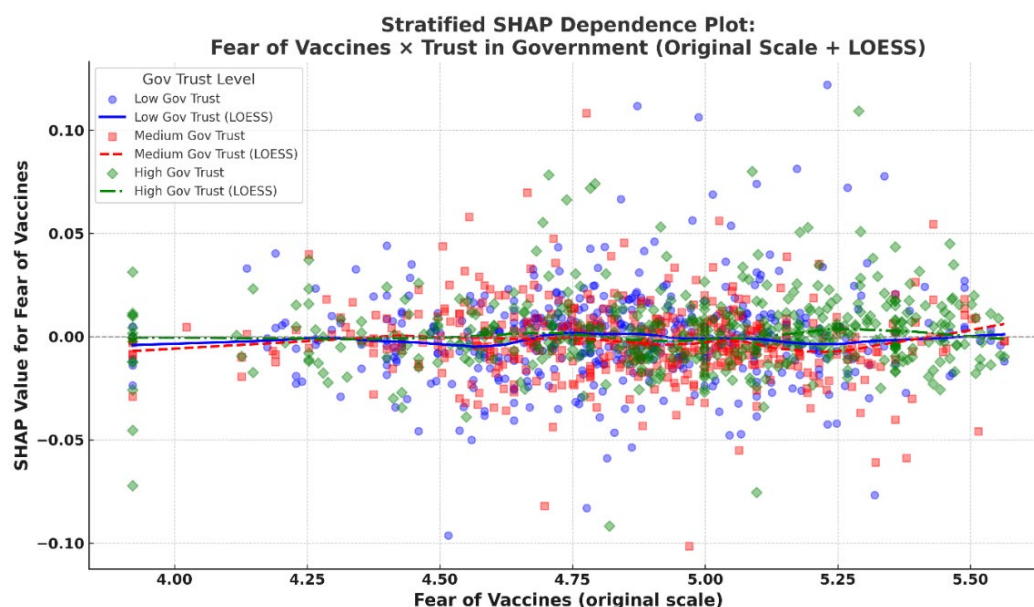


Source: Authors' own calculations.

Figure 6: Interaction between general trust and trust in government.

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.



Source: Authors' own calculations.

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

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 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 fear of vaccines has a consistently negative impact on 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.

6.6 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 of 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 distrust and above 5 is trust). Though, as it is moderated by trust in the government, we find that higher trust levels increase compliance. When people do not trust the government, their trust in others plays a stronger role in 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.

7. Conclusions

Over the past three decades, the study and measurement of well-being have undergone a significant transformation. In the 1990s and early 2000s, 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 and Oswald (1995) revealed the social and economic determinants of life satisfaction.

By the 2010s, the emergence of Big Data and digital tools enabled researchers to capture real-time indicators of emotional well-being. Studies such as Kahneman and 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.

As we reflect on the last three decades and move further into the 21st 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 2. 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 and influencing 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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Supplementary Information A

To derive our time-series data, which captures sentiment and emotions, we construct variables using Big Data by extracting tweets from Twitter. In our analysis, we extracted two sets of tweets based on keywords, one related to COVID-19 vaccines and the other related to the government. The tweets containing these words amounted to 1,047,000 tweets. We extracted all tweets according to specific geographical areas (country).

For COVID-19 vaccines, we extract tweets using the keywords: *vaccinate, vacc, vaccine, Sputnik V, Sputnik, Sinopharm, Astrazeneca, Pfizer (if NEAR) vaccine, Pfizer-BioNTech, Johnson & Johnson, and Moderna.*

For the government, we extract tweets using the keywords: *government, parliament, ministry, minister, senator, MPs, legislator, political, politics, prime minister.*

The first step in our analysis is determining the tweets' language (we detected 64 different languages), and all non-English tweets were translated into English. After translation, we use NLP to extract the tweets' sentiment and underlying emotions. To test the robustness of coding the sentiment of the translated tweets, we use lexicons in the original language, if available, and repeat the process. We compare the coded sentiment of the translated and original text and find the results strongly correlated.

We make use of a suite of lexicons. Each differs slightly but primarily aims to determine the sentiment of unstructured text data. The two lexicons mostly used in our analysis are Sentiment140 and NRC (National Research Council of Canada Emotion Lexicon developed by Turney and Mohammad (2010)). The other lexicons are used for robustness purposes and are part of the Syuzhet package. The lexicons include Syuzhet, AFINN and Bing. The sentiment is determined by identifying the tweeter's attitude towards an event using variables such as context, tone, etc. It helps one form an entire opinion of the text. Depending on the lexicon used, the text (tweet) is coded. For example, if a tweet is positive, it is coded as 0; if neutral, 2; and if negative, 4.

We use the NRC lexicon to code the sentiment (as explained above) and analyse the underlying tweets' emotions. It distinguishes between eight basic emotions: anger, fear, anticipation, trust, surprise, sadness, joy and disgust (the so-called Plutchik (1980) wheel of emotions). NRC codes words with

different values, ranging from 0 (low) to 8 (the highest score in our data), expressing the intensity of an emotion or sentiment.

To construct the time-series data, we use the coding of the tweets and derive daily averages. In this manner, we derive a positive sentiment, a negative sentiment and eight emotion time series. We derive the sentiment time series using different lexicons as a robustness test and compare these results using correlation analyses. We perform additional robustness tests, for example, to determine whether the sampling frequency significantly influences the results.

To test the robustness of the *frequency*, we construct the relevant index (time series) per day (the norm); we repeat the exercise but construct the time series per hour. We find similar trends in our hourly and daily time series, indicating that the timescale at which sampling occurs does not significantly influence the observed trend.

To test whether the *volume* of tweets affects the derived time-series data, we extract random samples of differing sizes from the daily text corpus of tweets. The time series based on these smaller samples (50 per cent and 80 per cent of the daily extracted tweets) are highly correlated to the original time series.

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Supplementary Information B

Phases per country	Date	Eligible population	Total population 2021
Australia			
Phase 1a Began in late February 2021, targeting quarantine and border workers, frontline healthcare workers, and aged care and disability residents and staff	22/02/2021	678000	25956000
Phase 1b Included adults aged 70 and over, Aboriginal and Torres Strait Islander people over 55, younger adults with underlying medical conditions or disabilities, and other critical and high-risk workers	22/03/2021	6100000	25956000
Phase 2a: Expanded to adults aged 50-69, Aboriginal and Torres Strait Islander people aged 18-54, and other critical and high-risk workers	1/05/2021	6500000	25956000
Phase 2b: Covered the remainder of the adult population	20/06/2021	6600000	25956000
Phase 3: Considered vaccination for individuals under 16 if recommended	15/08/2021	5600000	25956000
Belgium			
Phase 1a Residents and staff of nursing homes and long-term care facilities, frontline healthcare workers, and hospital staff.	5/01/2021	700000	11570000
Phase 1b Individuals aged 65 and over, people aged 45-64 with underlying health conditions, and essential workers.	1/03/2021	4500000	11570000
Phase 2a: The general adult population aged 18 and over.	1/06/2021	9251000	11570000
Phase 2b: Vaccination extended to 16-17-year-olds.	1/07/2021	258000	11570000
Germany			
Priority Group 1: Eligible Individuals: Persons aged 80 and above Residents and caretakers of senior facilities High-risk medical personnel	26/12/2020	8600000	83697000

Priority Group 2: Eligible Individuals: Persons aged 70 to 79 Individuals with high-risk preexisting conditions Caretakers of pregnant women Additional medical personnel not included in Group 1	1/02/2021	12000000	83697000
Priority Group 3: Eligible Individuals: Persons aged 60 to 69 Individuals with moderate preexisting conditions Employees in government, retail, vital infrastructure, and educators	1/04/2021	15000000	83697000
Priority group 4: Eligible Individuals: Remaining adult population aged 16 to 59 Individuals not included in the previous priority groups	7/06/2021	6517000	83697000
Spain			
Phase 1 Target Groups: Residents and staff of elderly and disabled care homes. Frontline healthcare and social care workers. Individuals with severe disabilities not residing in care homes.	27/12/2020	2500000	47735000
Phase 2 Target Groups: Individuals aged 80 and above. Individuals aged 70-79. Individuals aged 60-69. People with high-risk conditions. Other healthcare and social care professionals. Essential workers (e.g., police, firefighters, teachers).	1/03/2021	9000000	47735000
Phase 3 Target Groups: Individuals aged 50-59. Individuals aged 40-49. Individuals aged 30-39. Individuals aged 20-29. Individuals aged 12-19.	1/06/2021	30083000	47735000

Phase 4 Target Groups: Children aged 5-11 (following regulatory approval).	1/09/2021	3230000	47735000
France			
Phase 1: Target Groups: Residents and staff of nursing homes and long-term care facilities. Healthcare professionals aged 50 and over.	27/12/2020	1000000	66083000
Phase 2: Target Groups: Individuals aged 75 and over not residing in care facilities. Individuals with high-risk health conditions.	18/01/2021	5000000	66083000
Phase 3: Target Groups: Individuals aged 65 to 74. Individuals aged 50 to 64 with underlying health conditions. Essential workers in sectors such as education, security, and food services.	1/03/2021	12000000	66083000
Phase 4: Target Groups: All individuals aged 18 and over.	31/05/2021	52241000	66083000
Phase 5: Target Groups: Adolescents aged 12 to 17.	15/06/2021	4902000	66083000
Great Britain			
Phase 1: Priority Groups: Residents in care homes for older adults and their carers. All those aged 80 and over. Frontline health and social care workers.	8/12/2020	6000000	67668000
Phase 2: Priority Groups: All those aged 70 and over.	18/01/2021	5500000	67668000

Clinically extremely vulnerable individuals (excluding pregnant women and those under 16).			
Phase 3: Priority Groups: All those aged 65 and over. Individuals aged 16 to 64 with underlying health conditions. Unpaid carers and those in receipt of carer's allowance.	15/02/2021	7000000	67668000
Phase 4: Priority Groups: All those aged 60 and over.	1/03/2021	16590000	67668000
Phase 5: Priority Groups: All those aged 55 and over.	8/03/2021	20948000	67668000
Phase 6: Priority Groups: All those aged 50 and over.	15/03/2021	25529000	67668000
Phase 7: Priority Groups: All adults aged 40 to 49.	13/04/2021	8590000	67668000
Phase 8: Priority Groups: All adults aged 30 to 39.	13/05/2021	9019000	67668000
Phase 9: Priority Groups: All adults aged 18 to 29.	18/06/2021	10160000	67668000
Phase 10: Priority Groups: All individuals aged 16 and 17.	4/08/2021	1516000	67668000
Phase 11: Priority Groups: All individuals aged 12 to 15.	13/09/2021	3246000	67668000

Italy			
Phase 1: Target Groups: Healthcare workers Residents and staff of nursing homes	27/12/2020	1900000	59729000
Phase 2: Target Groups: Individuals aged 80 and above Individuals aged 60-79 Individuals with high-risk health conditions Essential workers (e.g., school staff, police, armed forces)	1/02/2021	20000000	59729000
Phase 3: Target Groups: General population aged 16-59 without underlying health conditions	1/06/2021	33434000	59729000
The Netherlands			
Phase 1: Target Groups: Healthcare workers in acute care settings. Residents and staff of nursing homes and long-term care facilities.	6/01/2021	500000	17730000
Phase 2: Target Groups: Individuals aged 60 and above, starting with the oldest age groups. Individuals with high-risk medical conditions. Other healthcare workers.	1/02/2021	5000000	17730000
Phase 3: Target Groups: Essential workers in sectors such as education, public transport, and law enforcement. Individuals aged 18-59 without high-risk medical conditions.	1/05/2021	7000000	17730000
Phase 4: Target Groups: General population aged 18 and over.	1/06/2021	14382000	17730000

Phase 5: Target Groups: Adolescents aged 12-17.	1/09/2021	1179000	17730000
New Zealand			
Phase 1: Target Groups: Border and managed isolation and quarantine (MIQ) workers. Frontline healthcare workers at higher risk of exposure.	20/02/2021	50000	5107000
Phase 2: Target Groups: High-risk frontline healthcare workers. Residents in high-risk settings such as aged care facilities. Older Māori and Pacific people living in crowded housing situations.	1/03/2021	480000	5107000
Phase 3: Target Groups: Individuals aged 65 and over. People with underlying health conditions. Disabled people. Caregivers of those in high-risk groups.	1/05/2021	1700000	5107000
Phase 4: Target Groups: General population aged 60 and over.	28/07/2021	1182000	5107000
South Africa			
Phase 1: Target Groups: Frontline healthcare workers	17/02/2021	1250000	61502000
Phase 2: Target Groups: Essential workers Individuals in congregate settings	17/05/2021	16600000	61502000

Persons aged 60 and above Persons aged 18 and above with co-morbidities			
Phase 3: Target Groups: General population aged 18 and above	20/08/2021	42086000	61502000
Phase 4: Adolescents Aged 12 to 17	20/10/2021	6301000	61502000

Supplementary Information C

Table C1. Features included in models.

Variable	Description	Coding	Source
Subjective measures			
Happiness GNH	Happiness	All SWB variables are continuous.	Greyling and Rossouw (2019)
Trust	The emotion general trust		Greyling and Rossouw (2019)
Trust Gov	The emotion trust in the government		Greyling and Rossouw (2019)
Fear Vac	The emotion fear towards the vaccine		Greyling and Rossouw (2019)
Within-country measures			
New deceased cases	Percentage of population	Percentage	World Health Organization (2023).
Stringency index	A composite measure of nine of the response metrics	<p>The nine metrics used to calculate the Stringency Index are school closures, workplace closures, cancellation of public events, restrictions on public gatherings, closures of public transport, stay-at-home requirements, public information campaigns, restrictions on internal movements, and international travel controls.</p> <p>The index on any given day is calculated as the mean score of the nine metrics, each taking a value between 0 and 100.</p>	Mathieu et al. (2021)
Face coverings	Policies on the use of facial coverings outside the home	<p>0 - No policy</p> <p>1 - Recommended</p> <p>2 - Required in some specified shared/public spaces outside the home with other people present or some situations when social distancing not possible</p> <p>3 - Required in all shared/public spaces outside the home with other</p>	Mathieu et al. (2021)

Variable	Description	Coding	Source
		people present or all situations when social distancing not possible 4 - Required outside the home at all times regardless of location or presence of other people	
International travel controls	Restrictions on international travel	0 - no restrictions 1 - screening arrivals 2 - quarantine arrivals from some or all regions 3 - ban arrivals from some regions 4 - ban on all regions or total border closure Blank - no data	Mathieu et al. (2021)
Income support	Record if the government provides direct cash payments to people who lose their jobs or cannot work. Note: only includes payments to firms if explicitly linked to payroll/salaries	0 - no income support 1 - government is replacing less than 50% of lost salary (or if a flat sum, it is less than 50% of median salary) 2 - government is replacing 50% or more of lost salary (or if a flat sum, it is greater than 50% of median salary) Blank - no data	Mathieu et al. (2021)
Between-country measures			
Population rural (Percentage of population in rural areas)	People living in rural areas as defined by national statistical offices. It is calculated as the difference between the total and urban populations.	Percentage	World Bank staff estimates based on the United Nations Population Division's World Urbanization Prospects (2018)
GDP per capita (US\$)	Per capita	Continuous	World Bank (2023)
Diabetes prevalence	Percentage of population	Percentage	World Bank (2023)
Population density	People per square kilometre of land area	Continuous	United Nations (2022)

Variable	Description	Coding	Source
Females as a percentage of the population	Females as a percentage of the total population	Percentage	World Bank (2018)
Nurses per 1000	Nurses per 1000	Continuous	Mathieu et al. (2021)
Health expenditure (USD)	Per capita	Continuous	World Bank (2023)

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Supplementary Information D

Table D1: Country-specific top five factors

South Africa	New Zealand	Germany	Spain	Australia	Belgium	Italy	Great Britain	France	The Netherlands
New deceased cases	Face coverings	New deceased cases	Stringency index	Stringency index	New deceased cases	New deceased cases	International travel controls	Happiness	Stringency index
Stringency index	Stringency index	Stringency index	New deceased cases	Income support	Stringency index	Stringency index	Stringency index	Trust	New deceased cases
Trust	Trust	Happiness	Trust	New deceased cases	Trust	Trust	New deceased cases	New deceased cases	Fear Vac
Fear Vac	Happiness	Trust	Happiness	Happiness	Happiness	Happiness	Trust Gov	Stringency index	Happiness
Happiness	Trust Gov	Trust Gov	Fear Vac	Face coverings	Trust Gov	Face covering	Fear Vac	Face covering	Trust Gov

Source: Authors' own calculations.

Table D2: Results from adding the "country" feature to cross-country analysis

Feature	Gain
New deceased cases	0.3202478
Stringency index	0.18664067
Rural area (sq/km)	0.17578456
Trust	0.06989495
Diabetics as % of the population	0.05575237
GDP per capita (\$US)	0.05239824
Happiness	0.03681567
Trust in government	0.02849244
Fear of the vaccine	0.02107972
Facial coverings	0.0161665
International travel controls	0.01175918
Nurses per 1000 people	0.01033976
Human capital index	0.01007916
Income support	0.00280901
Population density	0.0014423
Country	0.0002477
Health expenditure (\$US)	0.000049984

Source: Authors' own calculations.

Table D3: Robustness test on the order of the importance of the variables predicting compliance during times of crisis, with an 80:20 split.

Feature	Gain
New deceased cases as % of the population	0.30731596
Stringency index	0.19988894
Rural area (sq/km)	0.17530455
Trust	0.07228194
Diabetics as % of the population	0.06121114
GDP per capita (\$US)	0.05704183
Happiness	0.03353287
Trust in the government	0.029865
Fear of the vaccine	0.02429205
Females as % of the population	0.01367282
Facial coverings	0.01298092
International travel controls	0.00936332
Income support	0.00221899
Nurses per 1000 people	0.00092481
Population density	0.00009508
Health expenditure (\$US)	0.00000977

Source: Authors' own calculations.

Table D4: Robustness test on the order of the importance of the variables predicting compliance during times of crisis, using a 5-fold cross-validation.

Feature	Gain
New deceased cases as % of the population	0.30953588
Stringency index	0.20275034
Rural area (sq/km)	0.17567812
Trust	0.07106868
Diabetics as % of the population	0.06109429
GDP per capita (\$US)	0.05711256
Happiness	0.03563838
Trust in the government	0.02878605
Fear of the vaccine	0.02437311
Facial coverings	0.01357422
International travel controls	0.00935312
Females as % of the population	0.00740608
Income support	0.00250379
Nurses per 1000 people	0.00082359
Population density	0.00025876
Health expenditure (\$US)	0.00004303

Source: Authors' own calculations.