Psychological Predictors of Socioeconomic Resilience Amidst the Covid-19 Pandemic: Evidence from Machine Learning

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Author note. Abhishek Sheetal was supported by project P0035462, “Digital Transformation of Hong Kong Enterprises in the Greater Bay Area,” funded by the Project of Strategic Importance at PolyU scheme. All code is available at https://osf.io/d9u5k. The machine learning model was pre-registered at https://osf.io/pm7xf. Data for the Covid-19 normalcy index can be found at https://www.economist.com/graphic-detail/tracking-the-return-to-normalcy-after-covid-19. The World Values Survey data is available at https://www.worldvaluessurvey.org.

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Abstract

What predicts cross-country differences in the recovery of socioeconomic activity from the Covid-19 pandemic? To answer this question, we examined how quickly countries' socioeconomic activity bounced back to normalcy from disruptions caused by the Covid-19 pandemic based on residents' attitudes, values, and beliefs as measured in the World Values Survey (WVS). We trained nine pre-registered machine learning models to predict the rate at which various socioeconomic metrics (e.g., public transportation occupancy, cinema attendance) recovered from their Covid-19 lows based on the WVS. All models had high predictive accuracy when presented with out-of-sample data (*r*'s >=.83). Feature importance analyses identified five psychological predictors that most strongly predicted socioeconomic recovery from Covid-19: religiosity, liberal social attitudes, the value of independence, obedience to authority, and the Protestant work ethic. Although past research has established the role of religiosity, liberalism, and independence in predicting resilience, it has not yet considered obedience to authority or the Protestant work ethic. Thus, the current research suggests new directions for future work on resilience that may not be apparent from either a deductive or an inductive approach.

Keywords: resilience; Covid-19; machine learning; neural networks; deep learning

Public Significance

This research found that countries in which people are more religious, have greater respect for authority, and have more liberal social attitudes bounced back more quickly from the massive disruptions caused by Covid-19 pandemic. In contrast, societies that emphasized independence and the Protestant work ethic struggled to recover from the pandemic. Cultivating values associated with resilience could help societies recover quickly from future pandemics and other disasters.

Psychological Predictors of Socioeconomic Resilience Amidst the Covid-19 Pandemic: Evidence from Machine Learning

Covid-19 has caused millions of deaths, stress to public health systems, and significant disruption to many countries (Zhang et al., 2022). Between March and May 2020, most countries introduced lockdowns to stem the spread of Covid-19, which led to the collapse of socioeconomic activity. As lockdowns eased, vaccines became available, and the population gained immunity, society gradually returned to normal. However, there was also considerable variation in the speed of the recovery of socioeconomic activity—in some countries, major indicators of socioeconomic recovery, such as office occupancy and air travel, returned to pre-pandemic levels quickly, whereas in other countries, it took significantly more time (The Economist, 2022a). What cultural values enable countries to be socioeconomically resilient*,* that is, to quickly recover from an unprecedented global crisis (Bonanno, 2004; Infurna & Luthar, 2018)?

To answer this question, the present research used machine learning, which allowed an examination of the potential role of 555 values in explaining cross-country differences in socioeconomic resilience. We focused on the recovery of socioeconomic activities that were severely disrupted by Covid-19, including air travel, office occupancy, retail footfall, and the amount of time that people spent outside (Nicola et al., 2020). However, in contrast to cross-country investigations of psychological resilience (e.g., psychological distress; Chen & Bonanno, 2020), and economic resilience (e.g., decreased GDP; Kim et al., 2022), limited research has examined predictors of cross-country differences in socioeconomic resilience (e.g., foot traffic, return to work). An improved understanding of psychological factors that predict a faster recovery of socioeconomic activity would allow policymakers to prepare their countries for future pandemics (Yang et al., 2023). Socioeconomic resilience is at an intermediate level between psychological and economic resilience. For example, if people are psychologically resilient, they would be more likely to venture outside their homes once the threat has subsided (i.e., exhibit socioeconomic resilience), and when many people in the community resume their everyday lives, the country's economy would recover (e.g., exhibit economic resilience).

Existing research about the antecedents of socioeconomic resilience has largely been limited to within-country investigations (e.g., Bonaccorsi et al., 2021). Expanding the spatial scope of the investigation might reveal novel predictors (e.g., differences in cultural values) that are particularly relevant to between-country differences in socioeconomic resilience. Past studies have also focused on one or two outcomes of socioeconomic resilience at a time, even though there could be several relevant markers of resilience in a given domain (Infurna & Jayawickreme, 2019). Finally, most past research on socioeconomic resilience has focused on the role of structural factors (e.g., neighborhood density, Chapple et al., 2022) as opposed to psychological predictors, which are likely relevant to socioeconomic resilience just as they are relevant to individual resilience. For example, psychological variables such as collectivism, uncertainty avoidance, and trust in government predicted whether people wore face masks and engaged in social distancing during the pandemic (Feng et al., 2023); although these social behaviors were measured at the individual level, they collectively bolstered the recovery of communities' socioeconomic activity from Covid-19 disruptions (Dunphy et al., 2022). However, although we can indirectly link a few cultural values to some indicators of socioeconomic resilience, to our knowledge, past research has not directly investigated cultural values that predict resilience.

The current research also seeks to address potential shortcomings of the broader literature on resilience, which likely arise because of the cost and effort required to conduct studies on individual resilience. For example, resilience studies typically span between 3 months and 1 year following the adverse event (Infurna & Jayawickreme, 2019), which may or may not be enough time for recovery and post-recovery growth. The number of assessments made in past studies is also sparse, so researchers cannot track the variability and trajectory of psychological outcomes between assessment time frames (Infurna & Jayawickreme, 2019). From a methodological and statistical perspective, the methods that resilience researchers tend to employ (e.g., growth-mixture modeling) rely on statistical assumptions that are not realistic (i.e., homogeneity of variance in trajectory slopes; Infurna & Luthar, 2017). Finally, although the study of resilience spans the basic and applied sciences (Norris et al., 2008), limited research has connected these disparate fields (Downes et al., 2013). By examining how psychological profiles measured at the individual level predict group-level socioeconomic recovery, our work contributes to a better interdisciplinary understanding of the antecedents of socioeconomic resilience.

We address these shortcomings by building a machine learning model of countries' socioeconomic resilience from Covid-19 based on residents' pre-Covid attitudes, values, and beliefs that were captured by the World Values Survey (WVS; Inglehart, 2020), a large survey dataset that sampled 400,000 respondents from over 100 countries across seven waves. To measure resilience, we employed daily archival data about 50 countries' socioeconomic activities that were significantly impacted by Covid-19 (e.g., cinema attendance, retail footfall). These 50 countries represent 75% of the world's population and 90% of its GDP (The Economist, 2022b). The dataset spanned about 2.5 years. Machine learning represents an ideal method for assessing population-wide predictors of countries' recovery trajectories following an adverse event. Machine learning models do not assume any functional form of the predictor-outcome relationship and do not make any statistical assumptions about the distribution of data, unlike traditional methods (Infurna & Luthar, 2017). Finally, the accuracy of the machine learning model's predictions is tested on a subset of the data to which the model was never exposed (i.e., the unseen data), thereby providing a metric of accuracy that is not vulnerable to overfitting.

Group Resilience

Since its conceptualization in psychiatry in the 1940s (Johnson & Wielchelt, 2004), resilience has been extensively investigated both at the individual level (e.g., individuals' psychological health; Bonanno et al., 2007) and at the group level (e.g., groups' ability to cope with disruptions; Adger, 2000). Because resilience has been studied in a wide range of disciplines (Manyena, 2006), it has been defined and operationalized in many ways (for reviews, see Folke, 2006; Gunderson, 2000). Relevant definitions of resilience include the "capability of a system to maintain its functions and structure in the face of internal and external change and to degrade gracefully when it must" (Allenby & Fink, 2000, p. 1034), the "ability of [a] system to withstand a major disruption within acceptable degradation parameters and to recover with a suitable time and reasonable costs and risks" (Haimes, 2009, p. 498), and the "system's ability to reduce efficiently both the magnitude and duration of deviation from targeted system performance levels" (Vugrin et al., 2010, p. 83).

Most of these definitions indicate two distinct components of group resilience (Hosseini et al., 2016). First, resilience can be understood as whether a group has the qualities and resources to minimize the negative impact of a disruption (also known as "reliability," "absorptive capacity," or "static resilience" e.g., Bruneau et al., 2003; Rose & Liao, 2005). For example, antecedents of communities' resilience include economic factors (e.g., employment, value of property), infrastructure (e.g., commercial and manufacturing establishments), social structure (e.g., number of faith-based organizations, age, race, gender of population), community capital (e.g., availability of counseling services), and institutional support (e.g., availability of emergency and hazards response plans, quality of zoning and building standards; Cutter et al., 2008). However, such studies have been criticized because decisions about which variables to include in these composite measures and how to weigh various indicators are subjective (Briguglio & Hohenegger, 2009) and may conflate cause and effect (Sensier et al., 2016).

Most definitions of resilience, however, focus on a system's ability to return to pre-disruption levels of activity (also known as "rapidity," "recovery, or "dynamic resilience," Henry & Ramirez-Marquez, 2012). Many researchers consider recovery critical to conceptualizations of resilience (Hosseini et al., 2016). Indeed, the word resilience originated from the Latin word "resiliere," which means to "bounce back." Thus, the common use of *resilience* implies the ability of an entity or system to return to normalcy after the occurrence of an event that disrupts its state. Consistent with this definition, researchers have operationalized resilience by examining the trajectory of relevant indicators pre- and post-shock (Hosseini et al., 2016). For example, resilience has been measured as the speed at which a country's building infrastructure returns to its pre-disruption state after an earthquake (Bruneau et al., 2003).

Socioeconomic Resilience Across Nations During Covid-19

Covid-19 severely disrupted various socioeconomic activities across the globe (Nicola et al., 2020). For example, in the hospitality and travel industry, hotel occupancy rates fell by 89% by the end of January 2020 in China (Hospitality Net, 2020). In the aviation industry, major airlines in the US sought a government bailout (Reuters, 2020). In the sports industry, many major sporting and cultural events, including the Euro 2020 soccer tournament, the Tokyo Olympics, and the Formula One Grand Prix, were postponed or cancelled (The Independent, 2020). Due to stay-at-home mandates, office occupancy, retail footfall, and cinema and restaurant attendance were reduced drastically (The New York Times, 2020). However, in the years following the initial disruption, there was also variability in how quickly countries' socioeconomic activity recovered (Lenton et al., 2022). For example, the slowest to recover were countries on the Asian Pacific rim (e.g., China, Vietnam) and New Zealand; the fastest to recover were countries in South America (e.g., Columbia), India, and the UAE (The Economist, 2022a). Nonetheless, few studies have examined factors that explain the large cross-country variation in recovery of socioeconomic activity from Covid-19 disruptions. Existing studies have been largely limited to within-country investigations, including recovery in office vacancy rates, retail spending, and public transportation ridership (Chapple et al., 2022), tourism (Zhang et al., 2022), human mobility (Bonaccorsi et al., 2021), highway traffic (Yang et al., 2023), and religious activity (Alahmadi et al., 2023). Studies have also examined the effects of structural predictors for socioeconomic resilience, such as income (Bonaccorsi et al., 2021), neighborhood density (Chapple et al., 2022), and the adequacy of medical resources (Yang et al., 2023). Finally, with a few exceptions (e.g., Chen & Quan, 2021), these investigations tend to focus on single (versus multiple) indicators of socioeconomic resilience.

In the present study, we assessed socioeconomic resilience using multiple measures of socioeconomic activity that were disrupted by Covid-19 (e.g., cinema, sports attendance, public transportation occupancy, how frequently retail stores were visited, and time spent outside) across 50 countries (*The Economist*, 2022b). These measures were tracked daily and scaled to the pre-pandemic level (which was designated at 100). Following past research (Bruneau et al., 2003; Cox et al., 2011), we operationalized resilience as the recovery slope for each country from the lowest point of economic activity since the pandemic was declared to the last available datapoint at the time of analysis. Although numerous economic and social structures undoubtedly explain between-country variation in the recovery slopes of socioeconomic resilience, in this research, we were interested in the predictive effects of cultural values.

Instead of basing our analysis on existing narrowly defined cultural dimensions (e.g., Hofstede's dimensions), we decided to consider the wide range of attitudes, values, and beliefs that have been measured in the World Values Survey (WVS). By doing so, we can greatly expand the explanatory scope of the current study. However, as the survey has over 500 intercorrelated measures that could be potentially relevant, deductive reasoning fails because no theory of culture considers such a wide range of values. Thus, we turned to machine learning, which allows us to engage in abductive reasoning instead of deductive reasoning. Recent research has used machine learning to generate novel hypotheses in psychology using the WVS (Sheetal et al., 2020, 2022). In these prior studies, the dependent variable was contained within the WVS, but in our case, the resilience metrics were obtained from an external source. We suggest that researchers do not have to restrict themselves to the outcome variables already available in large social science datasets. As long as a linking variable (e.g., respondents' country) is present, researchers can merge outcome variables from other datasets and then create a neural network to anticipate the outcome variable.

Machine learning for discovery hinges on two key methodological steps: (1) the proof of the pudding test, which guards against programming errors, overfitting, and underfitting; and (2) model unpacking, which helps identify the variables that contribute the most to the model's prediction (see Supplementary Materials). Useful machine learning models are those that are generalizable, that is, they can make accurate predictions when presented with new data (Barbiero et al., 2020). A generalizable model is one that is neither underfitted nor overfitted to the data on which it is trained. Because neural networks have millions of trainable parameters, they tend to be overparametrized, which means they are less likely to suffer from underfitting (Fu et al., 2022) but more likely to suffer from overfitting (Dar et al., 2021). Therefore, we took extra precautions to reduce the chances of overfitting when developing our neural networks, such as randomly dropping nodes in each layer (Srivastava et al., 2014).

Transparency and Openness

All code is available at the online data repository for this project (https://osf.io/d9u5k). The machine learning model was pre-registered (https://osf.io/pm7xf)

Method

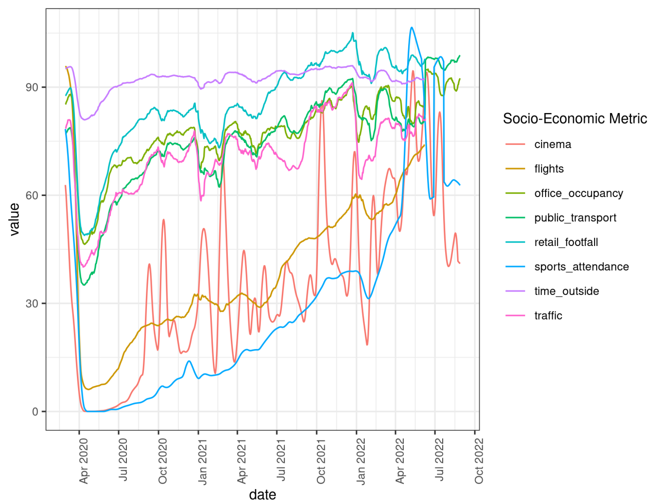
Dataset

Resilience

Rather than using survey measures of resilience in the form of recovery trajectories, we used secondary available data that assessed societies' socioeconomic recovery from disruptions caused by the Covid-19 pandemic. The relevant dataset for 50 countries, posted by *The Economist* (2022a), captured daily socioeconomic metrics from February 28, 2020, before Covid-19 was declared a global pandemic by the World Health Organization, to August 28, 2022 (when we commenced our data analysis). In this data, 100 refers to the pre-pandemic level of each socioeconomic activity. Eight different socioeconomic activities were tracked. The variable *cinema* was assessed via box office revenues (the weekly data was provided by websites such as Box Office Mojo). S*ports attendance* was assessed as attendance at professional sports events (provided by websites such as Transfermarkt). *Time spent outside* was aggregated at the country level (data was provided by Google). *Office occupancy* was measured as the footfall in the workplaces of the three largest cities (data was provided by Google). *Retail footfall* was measured in terms of footfall on “retail and recreation” sites (data was provided by Google). *Flights* were measured by the number of flights departing from domestic airports (data was provided by UN ICAO). *Public transport* was measured as footfall in the transport hubs of the three largest cities (data was provided by Google). Lastly, *traffic* was measured as the congestion levels in the three largest cities (data was provided by TomTom). *The Economist* also weighted the eight socioeconomic activities and developed an overall socioeconomic activity score. Although some countries did not have data on some of these eight socioeconomic activity measures, because the overall measure was based on a weighted average formula created by The Economist, the overall composite score was available for all countries as there is data on at least one measure of socioeconomic activity for each country.

Figure 1 plots the global recovery across the 50 nations on eight dimensions. All numbers showed a sharp decline across the spectrum of indicators after the World Health Organization declared Covid-19 a pandemic (BBC News, 2020), which halted the majority of international and domestic travel, forced the closure of the majority of non-essential businesses, and virtually all recreational activities. After that WHO announcement, lockdowns and self-isolations were either voluntarily instituted or mandated by the governments in the majority of the world. After April 2020, a consistent trajectory of recovery across resilience outcomes can be seen.

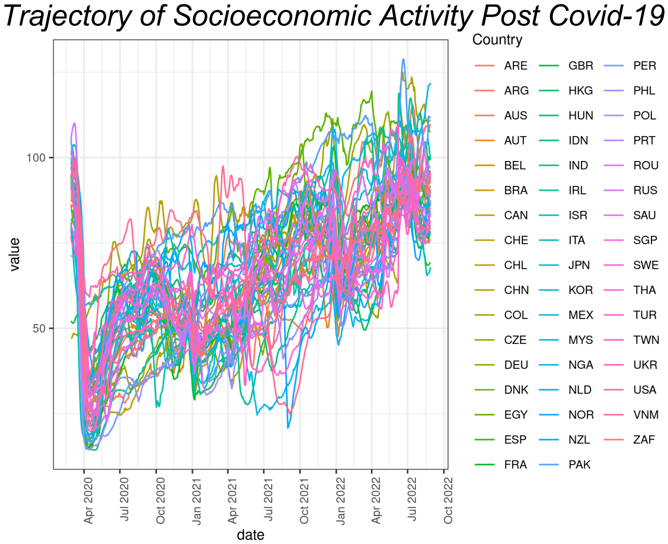
Figure 1
Trajectory of Socioeconomic Activity Post Covid-19 Across Time.



The aggregated socioeconomic activity of each of the 50 countries is depicted in Figure 2. One can notice that, despite an almost universal fall to near zero around the same time, these countries demonstrate starkly different levels of recovery with time. We thus used the varying slopes of each of these 50 countries as a proxy for resilience post-Covid-19. To measure the recovery slope for each country, we used dates on which the socioeconomic activity was the lowest as the starting point. We found that different countries went into a socioeconomic freeze on different dates between Feb 28, 2020 and June 30, 2020 (see Table S1 in the supplementary materials for the precise date for each country).

Figure 2

Trajectory of Socioeconomic Activity Post Covid-19 across Countries (three-letter ISO code)



There were considerable daily fluctuations in socioeconomic activities over time due to the arrival of new Covid-19 variants and sporadic removal and reimposition of lockdowns. Despite these fluctuations, there is a general upward trend in socioeconomic activities. We define the relative resilience of a nation as the steepness of this upward slope. This slope is measured as the recovery angle from the date of the country's lowest economic activity until the last available datapoint on August 28, 2022. To determine the slope for each country for each of the nine dimensions, we fit a straight line from the lowest point of activity after the WHO announcement of the global pandemic to the last available data point at the time of our analysis. The sole predictor was time (the day with the lowest economic activity was coded as day 0, and all subsequent days were recoded as positive integers with reference to that date). The beta coefficient of time on each socioeconomic outcome was used as a proxy for resilience. Table S2 in the supplementary materials presents each country's recovery slopes on the eight measures of economic activity and orders them by their level of socioeconomic resilience, as indicated by their overall composite score. The most resilient regions (i.e., those with the largest positive slope) are at the top (i.e., Columbia, India), and the least resilient regions (i.e., those with the smallest positive slope) are at the bottom (i.e., New Zealand, Vietnam, China, and Taiwan).

Psychological Predictors of Socioeconomic Resilience

Covid-19 caught many social science researchers and governments by surprise. Researchers did not have time to design studies that would assess the effect of various predictors on resilience in the life cycle of the Covid-19 pandemic. Our goal was to identify a set of socio-cultural attitudes, values, and beliefs that likely predict cross-country recovery from Covid-19. In the absence of studies that periodically measured psychological predictors of socioeconomic resilience during the Covid-19 pandemic, we employed survey data that was collected just before the pandemic, specifically the World Values Survey data (WVS; Inglehart, 2020). We used Wave 7 of the WVS data, version v1.2 downloaded on July 3, 2021, which sampled 69,578 individuals from 48 countries between 2017 and 2019. We did not use earlier data from the WVS because prior research has identified discernible changes in cultural attitudes, values, and beliefs over the years (Sheetal & Savani, 2021). Hence, we focus on survey data that were collected just before the Covid-19 pandemic.

The Final Dataset

The number of countries that overlapped between the Economist dataset and the WVS Wave 7 dataset is indicated in Table 1. We assigned each WVS respondent from these overlapping countries a set of nine resilience numbers based on their country. The predictors were the attitudes, values, and beliefs of these respondents that could plausibly serve as predictors of resilience (see file CR.xlsx on OSF for variables that were included in the analysis; see the pre-registration for additional information). We built nine predictive models, one for each outcome listed in Table 1. For each outcome, we randomly split the data into two parts: 90% of the data was used to build the predictive model, and the remaining 10% of the data was used to test the generalizability of the model as well as to assess overfitting and underfitting.

Table 1

Final Sample for This Study

Outcome	Cinema	Flights	Office Occupancy	Public Transport	Sports Attendance	Time outside	Retail footfall	Traffic	Overall
Countries	24	25	23	24	15	25	25	22	26
N	39,667	39,641	36,428	39,464	26,649	39,641	39,641	37,000	42,677
Predictors	555	555	555	555	555	555	555	555	555

Predictive Model Building

Using the training data, we built nine neural networks to predict resilience outcomes from the 555 WVS predictors. We adapted the *R* code and method of Sheetal et al. (2020) for this purpose. The procedure to build the neural network model was pre-registered, and the relevant files were uploaded on OSF prior to model building. Table S3 in the Supplementary Materials lists the R code file that was used in each step of the model-building process. We report the predictive accuracy of the neural network on *unseen test data* using two metrics. First, we use the R^2 value, that is, the square of the correlation between the predicted and actual resilience scores. Second, we report Mean Absolute Scaled Error (MASE), which is a scale-free error metric and is “the best available measure of forecast accuracy” (Hyndman & Koehler, 2006, p. 682); “values of MASE greater than one indicate that the forecasts are worse, on average, than in-sample one-step forecasts from the naive methods,” such as those that combine Bayesian statistics with regression analyses (Hyndman & Koehler, 2006, p. 687; Thornton & Tamir, 2022). In other words, a good MASE score should be less than one. Finally, to assess whether our neural network models are underfitted, we also built nine parallel LASSO models using the training data. A LASSO model is robust against multicollinearity (Tibshirani, 1996) and overfitting (McNeish, 2015), and yet it is a simpler model than a neural network. As pre-registered, we only retained the more complex neural network if it had a higher unseen test accuracy than the simpler LASSO.

To identify which predictors made the biggest contribution, we use the locally interpretable model-agnostic explanations from the DALEX package in R (Biecek, 2018). The approach randomizes the values of each predictor (one at a time) across all observations and asks the neural network to make a prediction; this procedure is repeated 10 times. Based on the extent to which the neural network’s predictive accuracy drops across these synthetic datasets, DALEX identifies predictors that are most important to making accurate predictions.

Effect of Multicollinearity

While neural networks are not affected by multicollinearity during model development (Maliar et al., 2021), multicollinearity complicates the feature selection process. Optimal feature selection from a large number of features remains an unsolved problem in mathematics (Davies & Russell, 1994). Proposed approaches include manual feature selection (Alabsi et al., 2021), but this practice can introduce researcher bias. Because there is limited guidance on how to optimally select features in the presence of multicollinearity, we instead checked the extent to which multicollinearity affects our selected features. To do so, we built two additional models: Overall2, a model that utilizes all 45 top predictors from Table 3, and Overall3, a model that utilizes the remaining 510 predictors. We assessed the R2 of both Overall2 and Overall3 in the unseen data and compared them with that of the Overall model, which was built using all 555 predictors from the WVS. Finally, to assess the effect of multicollinearity, we compared the predictors yielded by the neural network model with the predictive effects yielded by ordinary linear regression (see Supplementary Materials). We found that the top predictors selected based on the neural network feature importance analyses were more stable and consistent than those identified by ordinary least squares regressions, indicating that our neutral network models are relatively less affected by multicollinearity.

Results

Table 2 lists the model's predictive accuracy when presented with the unseen data after the model was finalized (i.e., the proof-of-pudding test). A zero correlation would mean that the model was completely overfitted or fraught with programming errors. When presented with new data, our model could accurately predict the resilience outcomes (*r*'s >= .83). Nonetheless, we observed a decrease in all models' accuracy from the training data to the unseen data. For example, the *Overall* model's accuracy dropped from 94.1% in the training data to 79.2% in the unseen data.[1] We also find that the MASE scores for all neural networks are below one. Finally, although the LASSO models (built for comparison) also had numerically high accuracy in the unseen data, their accuracy y was consistently lower than that of the neural networks. Thus, our models learned generalizable relationships, and programming errors (if any) are of little consequence. Thus, our neural network models passed the proof-of-pudding test.

Table 2

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[1] A plausible explanation of the drop in accuracy between the seen and the unseen data is that the two distributions are non-identical. Achieving a perfectly stratified split is a difficult task (Uçar et al., 2020). Theoretically, the match between the seen and unseen data is likely higher if the data were split 50% seen and 50% unseen, but we had pre-registered a 90%-10% split. In addition, increasing the size of the unseen sample increases the risk that the training sample is too small, which means that the model would have low generalizability outside the dataset (Raudys & Jain, 1991).

Model Statistics in the Unseen Data

	Cinema	Flights	Office Occupancy	Public Transport	Retail footfall	Time outside	Sports attendance	Traffic	Overall
Unseen *N*	3,946	3,942	3,598	3,904	3,942	3,942	2,611	3,702	4,248
Neural network MASE	0.31	0.34	0.28	0.33	0.29	0.35	0.32	0.32	0.26
Neural network *r*	0.83***	0.85***	0.90***	0.86***	0.87***	0.83***	0.84***	0.85***	0.89***
Neural network R^2	68.9% (94.1%)	72.3% (90.2%)	81% (90.2%)	74% (90.2%)	75.7% (92.2%)	68.9% (92.2%)	70.6% (94.1%)	72.3% (92.2%)	79.2% (94.1%)
LASSO *r*	0.63***	0.60***	0.68***	0.70***	0.71***	0.63***	0.65***	0.64***	0.71***
LASSO R^2	39.7% (57.8%)	36% (62.4%)	65.6% (64%)	49% (67.2%)	50.4% (68.9%)	39.7% (59.3%)	42.3% (65.6%)	41% (60.8%)	50.4% (68.9%)

Note. ****p* < .001; numbers in brackets are comparison metrics of the model on the training data.

Next, we proceed to unpack the model. This analysis identified the extent to which each of the 555 WVS variables contributed to predicting each of the nine resilience outcomes. The detailed results are uploaded on OSF (see the folder titled “Glass box results”). Table 3 presents the top ten predictors for each resilience outcome. Finally, to assess the effect of multicollinearity, we report the R^2 for three different *Overall* models in the unseen data. The *Overall* model with all 555 predictors had an R^2 of 79.04%. The model with the top 45 predictors covered in Table 3 (*Overall2*) had R^2 = 64.00%. The model with all remaining 510 predictors (*Overall3*) had an R^2 of 71.38%. This pattern indicates that much of the information contained in the top 45 predictors is also contained in the remaining 510 predictors, indicating multicollinearity. However, the accuracy of *Overall2*, which included only 45 predictors, was 90% as high as that of *Overall3*, which included 510 predictors, indicating the *Overall2* model is a more parsimonious model. This finding implies that the machine learning model was about to sort out more relevant from less relevant correlated variables. Next, we discuss predictors that recurred most frequently across the nine models in Table 3.

Respect for Authority Figures

The most important predictor of overall resilience, as well as of six of the eight resilience dimensions, was about respect for authority figures, which was associated with higher resilience. Several other top predictors were also related to this construct. Specifically, these predictors capture whether participants believed in the importance of fostering greater respect for authority in the future (variable *e018*) and the importance of instilling obedience in children (variable *a042*). People high in obedience to authority also tend to hold a stronger sense of national pride (variables *g006*), which again featured among the top 10 predictors. Constructs associated with respect for authority also predicted greater resilience on a number of sub-dimensions. Specifically, a greater sense of closeness with one's country (variable *g062*; Osborne et al., 2017) and being proud of one's language (variable g024_8) were associated with more sports attendance and resumption of flights. Notably, this seems like a novel predictor of socioeconomic resilience, as we could not identify past research in the resilience literature claiming that greater respect for authority is an antecedent of resilience.

Religiosity / Spirituality

The second most important set of predictors linked to overall resilience and to multiple sub-dimensions was associated with religiosity and spirituality. These predictors assessed the strength of respondents' religious beliefs, such as whether they felt that God was important in their lives (variable *f063*), whether they believed in hell (variable *f053*), and God (variable *f050*). Religiosity and spirituality are established predictors of resilience and post-traumatic growth at both the group and the individual level (Shaw et al., 2005). Churches and faith-based organizations often provide financial aid (Alawiyah et al., 2011) and social support to people and the communities they live in, and especially during times of crisis (such as the pandemic), leading to greater collective resilience (Infurna, 2021). Additionally, religious participation and attendance led to greater social interconnectedness, which in turn was associated with greater collective economic and social resilience after crises (Freedman, 2004). Predictors of religiosity/spirituality (variables *f028b*, *a040*, *f034_3*, *f034_1*, and *d017*) were also associated with more specific measures of resilience. Specifically, the frequency with which respondents engaged in various religious practices, such as praying (variable *f028b*), the belief that it was important for their children to have religious faith (variable *a040*), and the tendency to describe oneself as a religious person rather than a convinced atheist (variables *f034_1* and *f034_3*), were associated with faster recovery in sports attendance, traffic, and flight resumption.

Liberal Social Attitudes

The next most important set of predictors of overall resilience, and of multiple sub-dimensions, pertained to liberal social attitudes. Thus far, research has come to conflicting conclusions about how social attitudes are associated with resilience. This might have occurred because liberalism includes a wide range of social attitudes and economic policies (Inglehart & Baker, 2000). The "rigidity of the right" hypothesis in political psychology argues that groups with more liberal values should demonstrate greater collective resilience (Bonanno & Jost, 2006). Specifically, if liberal groups are less rigid and cynical than conservatives, liberal communities can develop more flexible, pragmatic, and adaptive coping strategies in the face of adversity (Bonanno & Jost, 2006). At the same time, conservative groups tend to be more obedient to authority and adhere to norms and rules (Gelfand et al., 2021), which should in theory lead to greater collective resilience. However, the machine learning findings indicate that the positive relationship between liberalism and collective resilience dominates.

Our analysis indicated that liberal social attitudes, such as being open to neighbors who are heavy drinkers (variable *a124_03*), people who have AIDS (variable *a124_07*), and unmarried couples living together (variable *a124_42*), were positively associated with overall composite resilience. However, we found mixed effects for specific resilience outcomes. Liberal attitudes, such as the belief that children should value tolerance and respect for other people (variable *a035*), the desire for greater income equality (variable *e035*), accepting gay people as neighbors (variable *a124_09*), and the belief that the death penalty is not justifiable, were associated with faster recovery in flights flown, office occupancy, cinema attendance, time spent outside, and traffic. However, conservative attitudes, such as the belief that sex before marriage (variable *f135a*) and divorce (variable *f121*) were not justifiable, the belief that immigrants do not promote cultural diversity (variable *g054*), the belief that immigrants were more likely to take away scarce jobs (*c002*), increase unemployment (variable *g059*), and that immigration would lead to social conflict (variable *g060*), were associated with faster recovery in retail footfall, time spent outside, office occupancy, flight resumption, and use of public transport. Overall, our mixed findings about liberal attitudes were consistent with the mixed findings in the literature.

Emphasis on Hard Work / Protestant Work Ethic

The next set of predictors associated with overall resilience referred to the importance of hard work in children (variable *a030*) and placing less emphasis on hard work in the future (variable e015). These constructs are related to the Protestant work ethic (Weber, 1930) and the Confucian work ethic (Lim, 2003), both of which emphasize diligence and personal responsibility. Specifically, a greater emphasis on hard work is associated with lower resilience. This is a surprising finding that has not yet been documented in the resilience literature.

Independence

The final set of predictors associated with several resilience sub-dimensions (but not with overall resilience) was associated with independence. Specifically, the importance of independence in children (variable *a029*) was associated with a lower recovery in time spent outside and in traffic. One of the core ideas of independence is self-interest, which justifies the pursuit of personal goals at the expense of the collective (Triandis, 1989). People in more independent cultures were less willing to follow social distancing recommendations, which led to prolonged infections (Feng et al., 2023). More generally, independent groups may be less able to coordinate with each other to quickly recover from crises.

Varying Predictive Effects Across Multiple Domains of Resilience

Finally, we found that certain predictors had positive effects on some measures of resilience and negative effects on other measures (Infurna & Jayawickreme, 2019). This is an important finding because if researchers examined only one outcome, such as cinema attendance, they would have drawn very different conclusions about what would be beneficial for resilience than if they examined resilience across multiple domains. Specifically, we found that having stronger religious beliefs (variables *f063* and *f050*) and engaging in frequent prayer (variable *f028b*) were associated with a faster recovery in traffic and sports attendance but slower recovery in cinema attendance. Being open to having homosexuals as neighbors (variable *a124_09*) was associated with faster recovery in spending time outside, traffic, and cinema attendance but a slower recovery in retail footfall. Placing less emphasis on hard work in the future (variable *e015*) was associated with faster recovery in sports attendance and use of public transport but slower recovery in traffic. Finally, the belief that it is justifiable to beat children (variable *f114c*) was associated with faster recovery in retail footfall but slower recovery in cinema attendance and time spent outside. Future research is needed to assess whether these differential relationships are replicable and to explain them.

Discussion

The present research yields two key insights. First, we found that based on residents' attitudes, values, and beliefs measured before the pandemic, neural network models could explain a substantial proportion of the variance in countries' objective socioeconomic resilience from the Covid-19 pandemic across nine dimensions, with R^2 > 68%. This finding indicates that cultural values play a significant role in predicting socioeconomic resilience. Indeed, if countries' socioeconomic resilience was primarily determined by economic or sociostructural factors rather than by cultural values, then our models would not have been able to explain a majority of the variance in countries' resilience. Additionally, the current research has identified cultural values as the most important predictors of socioeconomic resilience. Three of these (i.e., religiosity/spirituality, independence, and liberalism) have been discussed in the broader resilience literature, whereas the other two (i.e., obedience to authority and emphasis on hard work / the Protestant work ethic) appear to be less studied. Therefore, the present research contributes to the existing literature by uncovering novel predictors of socioeconomic resilience.

The relationship between Protestant Work Ethic beliefs and lower group-level socioeconomic resilience may best be understood within the context of research about independence. Among the many factors that transformed societies into being culturally independent (Kitayama & Uskul, 2011), possibly the single most significant event was the advent of Protestantism in Western Europe (Sanchez-Burks, 2002), which then spread to North America to form contemporary individualism in the United States (Kitayama et al., 2009). Therefore, it seems reasonable that some of the core ethos of Protestant Work Ethic, including a weaker focus on relational concerns and a stronger focus on an individualistic way of being (Sanchez-Burks, 2002), would be associated with a greater collective reluctance to adhere to governmental regulations that can reduce transmission of Covid-19 and thus a slower recovery.

Although researchers have not considered the relationship between obedience to authority and resilience, these findings make sense when considered from the perspective of evolutionary psychology as well as within the specific context of Covid-19, during which governments around the world implemented various interventions (e.g., lockdowns, social distancing recommendations) to reduce transmission of Covid-19. Charles Darwin (1871/2004, as cited in Cacioppo et al., 2011) noted that when considering the survival of the fittest, a group comprised of members who obediently follow the group's goals and who are more willing to help other group members and to make sacrifices for the group would be more resilient. Within the context of Covid-19, a country comprised of citizens who respect and obey authority figures may be more resilient during the pandemic because people might be more likely to obey directives intended to reduce the transmission and spread of the virus, even though doing so constrains individual choice and freedom (e.g., through the use of social distancing guidelines and mask mandates; Feng et al., 2023). These findings also converge with research indicating that Covid-

19 mortality is lower in countries where people have higher trust and confidence in organizations (i.e., those who have confidence in the government, Lenton et al., 2022).

In addition to identifying which psychological factors were important predictors of resilience, the present analysis also identified variables that were not. For example, some of the notable predictors of psychological resilience at the individual level, including optimism (variable *b017*, Taylor & Armor, 1996), did not feature among the top ten predictors. Similarly, despite well-documented findings about how social support buffers the negative effects of stressful events (Cohen & Wills, 1985), the strength of social ties (e.g., variables *a057*, *a058*, and *a059*; measured in the WVS by how frequently participants spent time with their family, friends, and colleagues) did not emerge as a strong predictor of socioeconomic resilience. Finally, being in good physical health (variable *a009*) also did not feature among the top-ranked predictors (Mancini & Bonanno, 2009). One explanation is that these factors are particularly relevant for individual resilience but less so for group resilience.

Limitations and Future Directions

Our finding that the same predictors have positive effects on some resilience outcomes but negative effects on other outcomes supports the importance of measuring resilience across multiple domains (Infurna & Jayawickreme, 2019). However, it is unclear why these opposing effects arise. One possibility is that some socioeconomic activities pertained to engagement in leisure activities (e.g., sports game attendance, cinema, retail footfall) whereas others were not (i.e., office occupancy, traffic, use of public transport). These differences could explain why some predictors, such as a lower Protestant work ethic, were associated with greater sports attendance but lower routine or work-relevant resilience (e.g., use of public transport and traffic). Therefore, it would be crucial to conduct follow-up studies to validate the current findings to examine the psychological mechanisms underpinning them.

As unraveling a machine learning model is not settled science (Hall, 2018), it would be important to use the insights from our neural networks as plausible hypotheses that require future validation. For example, although the current research has verified that our neural networks can accurately predict the outcome variables in unseen data, it has not provided an external test of the top predictors of resilience identified by our model. Thus, future research needs to validate the current findings on an external, independently collected dataset. In addition, future research needs to validate that groups in which people emphasize obedience and respect for authority and score low on the Protestant work ethic are indeed more resilient after a setback. Another limitation is that WVS measures lack psychometric validity. This is because rather than measuring a smaller selection of constructs using many questions that can be averaged to form a scale, the WVS researchers developed the survey to examine many different constructs to optimize the breadth of coverage. This meant that we had to interpret individual scale items instead of using scores derived from well-established psychometric scales. To address this limitation, future research can replicate our findings using established scales. Finally, the current view in the literature is that optimal feature subset selection from a wide range of features is a mathematically unsolved problem (Gheyas & Smith, 2010); hence, we cannot categorically say that the chosen predictors are the objectively best antecedents of resilience from all the possible antecedents included in the WVS.

As noted earlier, there have been many definitions and operationalizations of resilience. To broaden the impact of the present work, future research could also employ machine learning methods to examine the generalizability of our predictors by assessing socioeconomic resilience in contexts other than Covid-19. For example, do the cultural values examined in this research also predict faster recovery from ecological disruptions (e.g., earthquakes and hurricanes), economic disruptions (e.g., unexpectedly high inflation), and social disruptions (e.g., depopulation)? Furthermore, research on resilience is often biased toward indicators that can be readily calculated using publicly available data (Rose & Krausmann, 2013), so future research needs to assess whether the findings replicate using more subtle measures of socioeconomic resilience (e.g., those gleaned from social media).

Finally, future research needs to examine whether the present findings generalize to the individual level, especially in the context of post-traumatic growth. For example, future research could test whether the cultural values identified in this study also predict psychological recovery from distressing events (e.g., job loss). This is important because it is possible that the values identified in our study might be especially relevant when groups cope with negative events that have a social transmissibility component (e.g., pandemics), but less so for other types of disruptions. Additionally, our measures of behavioral resilience were aggregated at the country level, so it is not clear whether the relationship between cultural values and country-level resilience would generalize at the individual level. Thus, future research needs to test whether the current findings replicate at the individual level. Future research also needs to examine whether the present findings generalize to post-traumatic growth. For example, after the pandemic, countries such as Denmark, Norway, and Sweden ended up with *higher* socioeconomic activity than they had before the pandemic (The Economist, 2022a). Therefore, it would be interesting to test whether the set of predictors identified in the focal research might also predict continued growth in socioeconomic activity once the stressor has been removed.

In conclusion, in examining predictors of countries' socioeconomic resilience, our machine learning approach affirmed the importance of cultural values, which could explain a majority of the between-country variance in eight objective indicators of socioeconomic resilience from the Covid-19 pandemic. Beyond verifying the predictive effects of previously theorized sociopsychological predictors of resilience (e.g., religiosity, liberal social attitudes, and independence), this research also uncovered potentially novel predictors (i.e., obedience to authority, Protestant work ethic). Thus, this research demonstrates that a machine learning-based predictive modeling approach can complement traditional theory-driven approaches to generate novel insights that might be overlooked by researchers (Sheetal et al., 2020).

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Table 3

Top Predictors of Resilience from the World Values Survey

Rank	Cinema	Flights	Office Occupancy	Public Transport	Retail Footfall	Time Outside	Sports Attendance	Traffic	Overall
1	e018: Future changes: Greater respect for authority (-0.16)	e018: Future changes: Greater respect for authority (-0.54)	a124_07: Neighbours: People who have AIDS (-0.49)	e018: Future changes: Greater respect for authority (-0.44)	d017: Ideal number of children (0.74)	e018: Future changes: Greater respect for authority (-0.38)	e018: Future changes: Greater respect for authority (-0.63)	e018: Future changes: Greater respect for authority (-0.28)	e018: Future changes: Greater respect for authority (-0.52)
2	f063: How important is God in your life (-0.06)	f034_1: Religious person: A religious person (0.56)	e018: Future changes: Greater respect for authority (-0.22)	a042: Important child qualities: obedience (0.66)	f121: Justifiable: Divorce (-0.51)	A124_09: Neighbours : Homosexuals (-0.43)	g062: How close you feel to your continent : How close you feel to your continent (-0.53)	a124_09: Neighbours: Homosexuals (-0.19)	f050: Believe in: God (0.74)
3	g052: Evaluate the impact of immigrants on the development of [your country] (-0.36)	g024_8: What thing are you proud of in your country: Language (0.47)	a040: Important child qualities: religious faith (0.46)	f050: Believe in: God (0.67)	f053: Believe in: hell (0.49)	f114c: Justifiable: Parents beating children (-0.31)	g024_8: What thing are you proud of in your country: Language (0.30)	f053: Believe in: hell (0.39)	a124_07: Neighbours : People who have AIDS (-0.47)

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Top Predictors of Resilience from the World Values Survey

Rank	Cinema	Flights	Office Occupancy	Public Transport	Retail Footfall	Time Outside	Sports Attendance	Traffic	Overall
4	f114c: Justifiable: Parents beating children (-0.34)	a042: Important child qualities: obedience (0.59)	a124_42: Neighbours: Unmarried couples living together (-0.22)	f053: Believe in: hell (0.54)	a124_07: Neighbours : People who have AIDS (-0.21)	a124_07: Neighbours : People who have AIDS (-0.53)	f028b: How often to you pray (-0.72)	A030: Important child qualities: Hard work (-0.25)	f063: How important is God in your life (0.70)
5	f144_02: Justifiable: Death penalty (-0.20)	a124_07: Neighbours: People who have AIDS (-0.25)	g054: Effects of immigrants on the development of [your country]: Strengthen cultural (-0.43)	f063: How important is God in your life (0.67)	f063: How important is God in your life (0.75)	A030: Important child qualities: Hard work (-0.28)	f063: How important is God in your life (0.72)	a124_07: Neighbours: People who have AIDS (-0.12)	a030: Important child qualities: Hard work (-0.19)
6	f028b: How often to you pray (0.08)	g062: How close you feel to your continent (-0.47)	a124_03: Neighbours: Heavy drinkers: (-0.61)	g006: How proud of nationality (-0.34)	f135a: Justifiable: Sex before marriage (-0.47)	a029: Important child qualities: independence (-0.47)	e015: Future changes: Less importance placed on work (0.08)	a029: Important child qualities: independence (-0.15)	a042: Important child qualities: obedience (0.63)
7	a124_09: Neighbours: Homosexuals: (-0.45)	f034_3: Religious person: A convinced atheist (-0.54)	f063: How important is God in your life (0.54)	g059: Effects of immigrants: Increase unemployment (0.48)	f114c: Justifiable: Parents beating children (0.24)	f050: Believe in: God (0.43)	a042: Important child qualities: obedience (0.49)	f028b: How often to you pray (-0.51)	g006: How proud of nationality (-0.33)

Table 3

Top Predictors of Resilience from the World Values Survey

Rank	Cinema	Flights	Office Occupancy	Public Transport	Retail Footfall	Time Outside	Sports Attendance	Traffic	Overall
8	a029: Important child qualities: independence (-0.03)	c002: Jobs scarce: Employers should give priority to (nation) people than immigrants (0.14)	e035: Income equality (-0.47)	a124_07: Neighbours: People who have AIDS (-0.31)	e018: Future changes: Greater respect for authority (-0.56)	a124_03: Neighbours: Heavy drinkers (-0.59)	f050: Believe in: God (0.74)	f050: Believe in God (0.51)	f053: Believe in: hell (0.51)
9	g061_2: Let immigrants come as long as there are jobs available (0.42)	a040: Important child qualities: religious faith (0.46)	a042: Important child qualities: obedience (0.32)	a030: Important child qualities: Hard work (-0.12)	a124_09: Neighbours: Homosexuals: (0.05)	g054: Effects of immigrants on the development of [your country]: Strengthen cultural (-0.29)	a030: Important child qualities: Hard work (-0.12)	f034_1: Religious person: A religious person (0.45)	a124_42: Neighbours: Unmarried couples living together (-0.11)

Table 3

Top Predictors of Resilience from the World Values Survey

Rank	Cinema	Flights	Office Occupancy	Public Transport	Retail Footfall	Time Outside	Sports Attendance	Traffic	Overall
10	g060: Effects of immigrants on the development of [your country]: Lead to social conflict (0.26)	a035: Important child qualities: tolerance and respect for other people (0.16)	f050: Believe in: God (0.67)	e015: Future changes: Less importance placed on work (0.08)	g006: How proud of nationality (-0.54)	f053: Believe in: hell (0.08)	a124_07: Neighbours: People who have AIDS (-0.44)	e015: Future changes: Less importance placed on work (-0.30)	a124_03: Neighbours: Heavy drinkers (-0.58)

Note. The number in parentheses is the correlation between the country-level average of each predictor and the recovery outcome. The sign represents the direction of the correlation. A number of items were reverse-scored in the WVS. Cells shaded green refer to predictors related to religiosity / spirituality; shaded blue, independence; shaded yellow, liberal attitudes; shaded red, respect for authority, shaded pink, emphasis on hard work, and unshaded, other constructs.