Original Paper

Developing an Interdisciplinary Framework for Behavioral Data Collection to Advance Coupled Behavioral-Epidemic Models: Cross-Sectional Study in 6 European Countries

Vittoria Offeddu[1*], PhD; Elisabetta Colosi[1*], PhD; Lorenzo Lucchini[1,2,3], PhD; Laura P Leone[1,4,5], MSc; Chiara Chiavenna[1,2], PhD; Duilio Balsamo[1,2], PhD; Elena D'Agnese[1,6,7], MSc; Francesco Bonacina[1], PhD; Maria Cucciniello[1,2], PhD; Filippo Trentini[1], PhD; Alberto Aleta[8,9], PhD; Piero Manfredi[6], PhD; Yamir Moreno[8,9], PhD; Márton Karsai[10,11], PhD; Vittoria Colizza[12], PhD; Júlia Koltai[13,14], PhD; Alessia Melegaro[1,2], PhD

[1]Health Emergencies Analytics Lab (HEAL), DONDENA Centre for Research on Social Dynamics and Public Policy, Bocconi University, Milan, Italy
[2]Bocconi Institute for Data Science and Analytics (BIDSA), Bocconi University, Milan, Italy
[3]Center for Health Emergencies, Fondazione Bruno Kessler, Trento, Italy
[4]Nuffield College, University of Oxford, Oxford, United Kingdom
[5]Department of Sociology, University of Oxford, Oxford, United Kingdom
[6]Department of Economics and Management, University of Pisa, Pisa, Italy
[7]Department of Statistics, Computer Science, Applications "Giuseppe Parenti", University of Florence, Florence, Italy
[8]Department of Theoretical Physics, Faculty of Sciences, University of Zaragoza, Zaragoza, Spain
[9]Institute for Biocomputation and Physics of Complex Systems (BIFI), University of Zaragoza, Zaragoza, Spain
[10]Department of Network and Data Science, Central European University, Vienna, Austria
[11]HUN-REN Rényi Institute of Mathematics, Budapest, Hungary
[12]Sorbonne Université, INSERM, Sorbonne Public Health Institute, Sorbonne Université Modeling Outbreaks Center (SUMOC), Paris, France
[13]MTA-TK Lendület "Momentum" Digital Social Science Research Group for Social Stratification, ELTE - Center for Social Sciences, Budapest, Hungary
[14]Institute of Empirical Studies, Faculty of Social Sciences, Eötvös Loránd University, Budapest, Hungary
*these authors contributed equally

Corresponding Author:

Alessia Melegaro, PhD
Health Emergencies Analytics Lab (HEAL), DONDENA Centre for Research on Social Dynamics and Public Policy
Bocconi University
via Röntgen 1
Milan 20136
Italy
Phone: +39 347 6724239
Email: alessia.melegaro@unibocconi.it

Abstract

Background: Human behavior influences infectious disease spread and the effectiveness of public health interventions. However, behavioral dynamics are often simplified in policy-oriented epidemic models, largely owing to the scarcity of suitable empirical data.

Objective: This study aimed to develop an interdisciplinary approach to collecting theory-grounded behavioral data on SARS-CoV-2 vaccination, capturing the complexity and temporal dynamics of preventive health behaviors while quantifying factors relevant to epidemic modeling.

Methods: We conducted a cross-sectional online survey of adults in France, Germany, Hungary, Italy, Spain, and the United Kingdom from March to July 2024, using age-, sex-, education-, and region-based quotas. Guided by both the capability, opportunity, motivation-behavior model and the requirements of epidemic modeling, we combined validated instruments with modeling-oriented measures in the questionnaire. We assessed temporal changes in retrospectively reported perceived COVID-19 severity and willingness to vaccinate across 5 time points, associations between vaccination willingness, uptake, and timeliness, and differences in behavioral indicators by vaccination status. To capture interactions relevant to both disease

transmission and information exchange, we measured age-specific in-person and discussion contacts. Selected measurements then informed a coupled behavioral-epidemic model to illustrate how intention-behavior gaps and changing intention shape simulated vaccination dynamics.

Results: After data quality filtering, 22,228 survey responses were analyzed. Vaccination willingness correlated with uptake and timeliness, although the proportion of initially unwilling respondents who received ≥2 vaccine doses ranged from 5.7% (95% CI 3.2%-8.3%) to 17.9% (95% CI 12.8%-23.1%) across countries. Respondents with low willingness delayed vaccination by approximately 2 months compared to those with high willingness (low willingness: 5.3 months, 95% CI 5-5.8; high willingness: 3.2 months, 95% CI 3-3.4). Respondents retrospectively reported declining perceived COVID-19 severity and willingness to vaccinate over time. Behavioral differences between vaccinated and unvaccinated respondents extended across 96% of the analyzed indicators (Wilcoxon rank-sum tests, $P<.001$) and were largest in the motivation domain. Vaccinated respondents reported higher vaccine confidence and trust in health authorities and lower concerns about vaccine safety. Average daily discussion contacts mirrored age-specific patterns of in-person contacts, ranging from 1.4 (95% CI 1.2-1.6) to 2.9 (95% CI 2.5-3.2) among adults aged <60 years across countries, compared with 0.5 (95% CI 0.4-0.6) to 1.2 (95% CI 1-1.4) among those aged ≥60 years. In model simulations, incorporating the intention-behavior gap increased vaccination coverage, while allowing willingness to change over time slowed uptake and reduced final coverage.

Conclusions: This interdisciplinary approach provides a practical route from behavioral theory to empirical measurements that inform states, transitions, vaccination and social contact processes in behavioral-epidemic models. By providing an empirical basis for representing behavioral heterogeneity and dynamics, this study reduces reliance on simplified behavioral assumptions, supporting the development of more realistic behavioral-epidemic models and effective response strategies.

J Med Internet Res 2026;28:e102346; doi: 10.2196/102346

Keywords: infectious diseases; human behavior; coupled behavioral-epidemic models; capability, opportunity, and motivation-behavior model; COM-B model; vaccination; cross-sectional studies

Introduction

Human behavior emerges from a complex interplay between social, economic, political, and environmental factors at the individual and community levels and varies significantly across countries, social groups, and over time [1]. In the context of infectious diseases, preventive health behavior both responds to and shapes epidemic conditions, revealing a dynamic and reciprocal relationship increasingly recognized over recent decades [2,3]. Changes in epidemic pressure can drive adherence levels to protective behaviors during an outbreak, such as self-isolation, social distancing, mask use, hygiene measures, or vaccine uptake [2,4]. In turn, the adoption or abandonment of these practices can impact disease transmission and reshape the effectiveness of infection prevention and control interventions.

Poorly understood or inadequately represented behavioral processes can compromise the development of public health measures. This limitation becomes particularly relevant when overly simplistic behavioral assumptions are used in the design and evaluation of interventions, for example when epidemic modeling tools are used [5,6]. Historically, the integration of behavior into epidemic models has prioritized tractability over social and psychological realism, often incorporating a single or very few behavioral factors at a time, such as cost-benefit [7,8], payoff [9,10], risk perception [11], awareness [12,13], or strategic social norms [9]. Even among the extensive body of work at the intersection of behavior and epidemiology prompted by the COVID-19 pandemic, explicit engagement with established psychological, social, and behavioral science theories remained limited [14-18], with only a small number of studies drawing on frameworks such as the Health Belief Model [19,20]. More commonly, human behavior was treated in epidemic models as an exogenous factor, incorporated through externally defined parameters [21,22]. Although these approaches have offered useful insights into selected aspects of the behavior-disease interaction [17], they often fail to capture the full scope of behavioral feedbacks operating in real-world settings. As a result, behavior remains a major source of uncertainty in epidemic projections [16,18].

These limitations have their roots in the limited investment made in interdisciplinary, theory-based, and modeling-oriented data collections to support the analysis of behavior-disease interactions [15,16,23,24]. Advancing policy-relevant research on behavior-disease interactions requires not only identifying who engages in a given behavior and why [6,25,26] but also quantitative measures of how frequently, for how long, with whom, and to what extent people adopt a given behavior across time and sociocultural contexts [23,27].

To fill this gap, we implemented an interdisciplinary framework grounded in the capability, opportunity, and motivation-behavior (COM-B) model [28] to collect comprehensive data on population- and context-sensitive factors potentially associated with preventive health behaviors. We investigated vaccination behavior across pandemic and endemic periods and for different diseases, including COVID-19, influenza, and measles in 6 European countries, namely France, Germany, Hungary, Italy, Spain, and the United Kingdom.

In this article, we present the study and use selected analyses to illustrate how the proposed framework addresses key data requirements for modeling behavioral-disease interactions. First, model-oriented behavioral data should distinguish psychological antecedents of behavior, such as intention or willingness, from observed behavior, because

their relationship with actual behavior is not straightforward and continues to be an area of active investigation [29]. We empirically quantified the discrepancy between willingness to vaccinate and observed vaccination behavior and further analyzed how varying levels of willingness influenced the timeliness of vaccination uptake. Second, model-oriented behavioral data should capture temporal and sociocultural variation in behavioral determinants, thereby avoiding unrealistically static representations of behavioral responses. We analyzed retrospective reports of perceived COVID-19 severity and willingness to vaccinate across 5 different time points anchored to key milestones of the COVID-19 vaccination campaign. Third, model-oriented behavioral data should characterize the social mechanisms underlying behavioral change. We illustrate how integrating behavioral theory with the requirements of epidemic modeling early in the data collection process can support the systematic investigation of both cognitive and social mechanisms through which behavioral choices are made and so facilitate the definition of novel, evidence-based endogenous behavioral responses, such as those prompted by peer exposure via discussion contacts. Finally, we demonstrate how behavioral data meeting these requirements can be directly translated into coupled behavioral-epidemic model components.

Methods

Instrumentation

We placed the dynamic relationship between human behavior and disease transmission at the core of the proposed interdisciplinary framework (Figure 1A). We used behavioral science investigation to capture behavioral complexity and state-of-the-art epidemic modeling to identify needs and data gaps.

Figure 1. Interdisciplinary framework for the collection and translation of empirical data into behavioral-epidemic models. (A) The framework centered on the dynamic relationship between human behavior and disease spread. (B) Behavioral outcomes of interest were first identified according to modeling needs, followed by the application of the COM-B model domains [28] (Table 1). Constructs were operationalized into measurable survey indicators through an iterative interdisciplinary process. Survey items were co-designed and validated to satisfy both behavioral and modeling requirements through expert review and cognitive interviews. (C) Country-specific data were collected from nationally representative samples, and extensive quality control checks were performed. (D) Empirical behavioral measurements were translated into model quantities that informed both the structure and the parameterization of coupled behavioral-epidemic models. COM-B: capability, opportunity, and motivation-behavior.

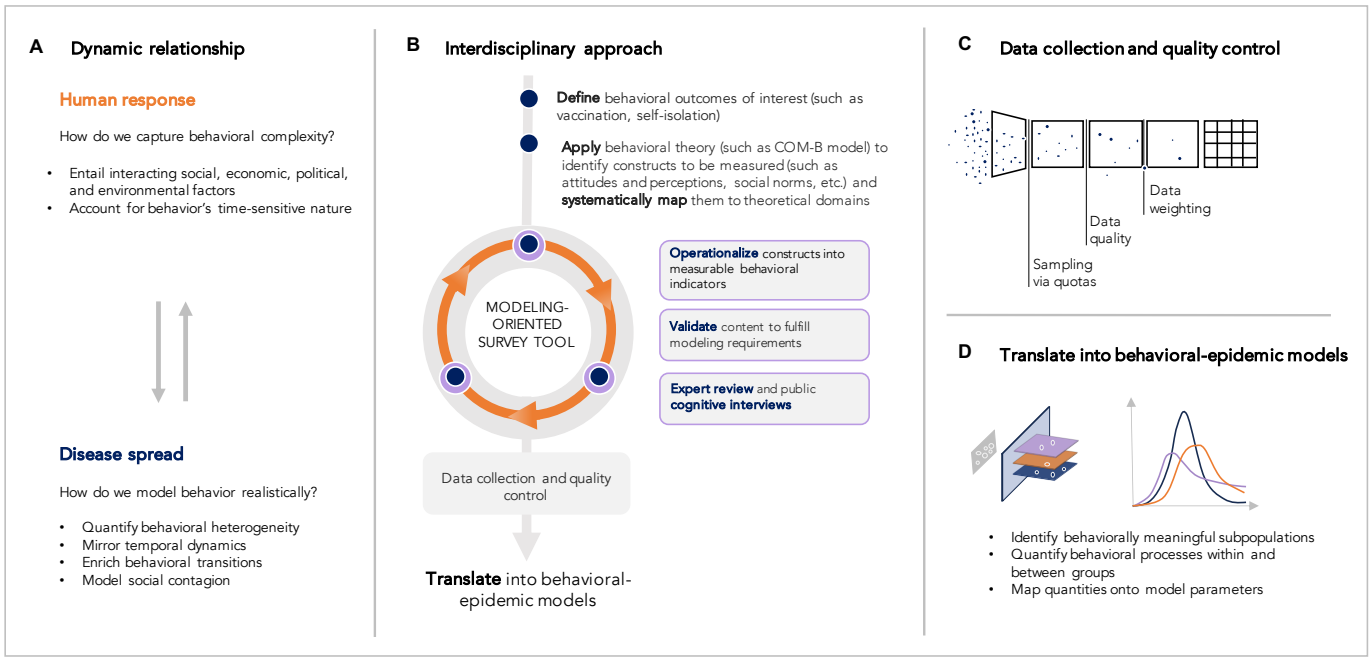


Table 1. Selection of factors potentially influencing COVID-19 vaccination behavior, stratified by the COM-B[a] model domains [28]. The survey instrument assessed each individual factor through one or more questions. For a full list of factors assessed in this study, please refer to Table S2 in Multimedia Appendix 1.

COM-B domains and components	Factors influencing vaccination behavior
Psychological capability: a person's social, emotional, and intellectual understanding, reasoning, and self-regulation abilities	
Level of knowledge	• Knowledge of infectious diseases • Knowledge of vaccines
Skills	• Ability to book vaccination appointments
Physical capability: a person's sensory and physical abilities	
Individual mobility	• Ease of reaching the nearest vaccination facility
Underlying health status	• Presence of medical contraindication(s) precluding vaccination
Physical opportunity: characteristics of a person's physical environment. It does not involve people or organizations but includes structural or logistical enablers or barriers	
Affordability	• Financial affordability • Time and personal resource constraints • Role of stress in preventing vaccination
Convenience	• Time and place convenience of vaccination offer
Social opportunity: characteristics of a person's social environment	
Peer influence	• Family members' and cohabitants' experience with COVID-19 illness and COVID-19 vaccination status • Number of relevant discussions with different social groups • Agreement with different statements related to vaccines among respondents' social groups
Trust in personal social environment[b]	• Trust in vaccination information from own social contacts • Trust in vaccination information from religious leaders
Automatic motivation: motivation that involves subjective wants and needs, impulses, and opposing impulses	
Risk perceptions of infectious diseases	• Perceived risk of infection with different pathogens • Perceived risk of severe health consequences from different infections
Risk perceptions of vaccines	• Perceived risk of severe health consequences from different vaccinations
Associative learning related to infectious diseases	• Own experience with COVID-19 illness and medical treatment • Experience with COVID-19 illness of people in respondents' social environment
Associative learning related to vaccination	• Own experience with vaccination side effects • Experience with vaccination side effects of people in respondents' social environment
Emotions	• Fear of different illnesses • Fear of different vaccines
Perceived health status	• Perceived overall health level
Reflective motivation: motivation to enact a behavior that involves judgments, intentions, evaluative beliefs, or mental plans	
Attitudes	• Vaccine confidence [30]
Trust in public sources and institutions	• Trust in governmental and public health institutions, health care professionals, and mass media
Moral values	• Respondents' moral values [31]
Opinions	• Agreement with different statements related to vaccines and opinion change over time
Prosocial behavior	• Presence of underlying health issues among cohabitants

[a]COM-B: capability, opportunity, and motivation-behavior.
[b]Trust in respondents' personal social environment was classified under social opportunity rather than reflective motivation because it is conditional on the presence and characteristics of respondents' social relationships and therefore reflects an attribute of their social environment rather than an individual motivational disposition.

Among the contemporary behavioral, psychological, and social science theories [32,33], we selected the COM-B model to investigate vaccination, which expands the definition of behavior beyond the traditional cognitive processes and provides guidance on how to structure comprehensive information on the potential psychological, physical, motivational, and environmental determinants of behavior [28]. This model has already been applied in several different settings to investigate vaccination [34-37] and other preventive health behaviors [38,39], and to inform the behavioral components of epidemic models [40]. Building on this literature, we developed a comprehensive cross-sectional survey instrument grounded in the COM-B model to capture the multidimensional drivers of vaccine uptake across 6 European countries. The mapping of behavioral constructs to the COM-B model was refined through iterative discussion among at least 3 authors with complementary expertise in behavioral science, epidemiology, and infectious disease modeling until consensus was reached (Figure 1B). In parallel, we assessed how key behavioral constructs could

be parameterized and tailored the data collection instrument to satisfy these predefined modeling requirements. While some questionnaire segments, such as those assessing vaccine confidence [30,41] or moral values [31], were constructed leveraging validated survey instruments, others were specifically designed to inform coupled behavioral-epidemic models. The complete workflow, from the identification of behavioral outcomes to data collection and the translation of measurements into epidemic model parameters using a modeling-oriented survey tool, is illustrated in Figure 1B. A full version of the questionnaire is available in Multimedia Appendix 2.

Quality of Measurements

The functionality and parsimony of the survey questionnaire were assessed by external experts in the fields of behavioral science, psychology, demography, political science, sociology, data science, infectious disease epidemiology, and modeling. In addition, qualitative cognitive interviews (n=11) were conducted with members of the general public recruited through flyers distributed in public spaces (Figure 1B). Interviewees spanned diverse age groups, genders, and educational characteristics. The cognitive interviews aimed to evaluate question clarity, interpretability, and relevance. Interviewees were asked to "think aloud" as they answered survey items, allowing us to identify ambiguities, assess comprehension, and refine wording to ensure consistent understanding across demographic groups. Comprehension and attention checks were incorporated into the survey to support the identification of potentially unreliable responses (see "Additional information" in Multimedia Appendix 1).

Conditions and Design

This was a nonexperimental, observational, cross-sectional study based on an online survey in France, Germany, Hungary, Italy, Spain, and the United Kingdom. No experimental conditions were manipulated, and participants were not assigned or randomized to study conditions. No deception was used, and masking was not applicable to this survey design. The study was preregistered on the Open Science Framework [42]. The 6 countries were selected to capture a diverse range of political systems, cultural contexts, epidemiological conditions, health care infrastructures, and vaccination policies within the European context.

Inclusion and Exclusion Criteria

Eligible participants were residents aged ≥18 years in each of the countries listed under Conditions and Design and registered members of online panels operated by the survey company selected for this study. Recruitment was conducted using quotas based on age, sex, educational attainment, and geographical distribution, as described under Sampling Procedures. Data-quality filters were applied to survey responses meeting the predefined completion threshold at the end of the substantive questionnaire to exclude invalid or implausible responses (Figure S1 in Multimedia Appendix 1). Only the optional questions concerning future recontact and social media handles followed this threshold. Records with inconsistencies affecting only specific sections of the survey were retained in the overall analytical sample and excluded only from analyses involving the affected items, as described under Data Diagnostics.

Respondents' Characteristics

The questionnaire gathered detailed information on respondents' sociodemographic, health, and economic characteristics, as well as location of residence, social identities, and compositions of household and social groups.

Sampling Procedures

Through a competitive announcement, we hired a professional survey company demonstrating compliance with the best scientific and ethical standards applicable to this research field and to all applicable national laws [43]. The company recruited study participants from its own country-specific online panels.

Participants were recruited using quota-based sampling, with quotas designed to approximate the national adult population by age, sex, educational level, and geographical distribution. Quotas were based on 2021 Eurostat statistics, datasets "Population on 1 January by age, sex and Nomenclature of Territorial Units for Statistics (NUTS) 2 region" and "Population in private households by educational attainment level - thousand persons" (the latest available data for the United Kingdom were from 2019) [44]. Educational levels were defined according to the International Standard Classification of Education [45], while geographical distribution followed the NUTS level-1 classification [46]. During data collection, the number of respondents in each category was compared with the corresponding official population statistics. If a subgroup was underrepresented, recruitment of participants in that population was intensified. Participation was voluntary among eligible members invited to participate. The participation rate could not be calculated because the number of panel members invited to participate by the survey company was not available to the research team.

Sample Size, Power, and Precision

The desired number of survey respondents for each country was calculated to detect a 5 percentage-point difference in the proportion of individuals willing to vaccinate with an additional vaccine dose between nonparents and parents, assuming a prevalence of 50% among parents. With a 2-sided α of 0.05 and 80% power (β=.2), the minimum required sample size was estimated to be 3317 individuals per country (1305 parents and 2012 nonparents). We therefore targeted at least 3500 valid responses per country, and recruitment continued until this target was reached. No interim analyses or outcome-based stopping rules were used. Achieved analytical sample sizes after data-quality filtering are reported in the Results section and in Figure S1 in Multimedia Appendix 1.

Measures and Covariates

The questionnaire comprised 91 variables covering behavioral outcomes and potential determinants. The primary outcomes

of the survey were the number of COVID-19 vaccine doses ever received by respondents and COVID-19 vaccination timeliness (Table S1 in Multimedia Appendix 1). Respondents were also asked to report the reasons for taking up, refusing, or interrupting COVID-19 vaccination. Secondary vaccination outcomes included willingness to get vaccinated against COVID-19 over time, influenza vaccine history during the 2020-2024 campaigns and before the COVID-19 pandemic, and consent to routine childhood vaccinations for one's children, if any. In addition, we investigated respondents' self-reported adherence to other protective behaviors at the time of the survey, including mask use and self-isolation when experiencing respiratory symptoms or mask use in crowded places when the epidemic pressure is high (Table S1 in Multimedia Appendix 1).

Factors within the COM-B model domains potentially associated with COVID-19 vaccination behavior are reported in Table 1. A full list of factors assessed in this study is provided in Table S2 in Multimedia Appendix 1.

To capture the time-sensitive nature of specific psychological constructs, respondents were asked to retrospectively report their "perceived risk from COVID-19" and "willingness to vaccinate against COVID-19" for 5 different time points: (1) before the introduction of COVID-19 vaccines; (2) when respondents were offered the 1st/2nd vaccine dose; (3) when respondents were offered the 3rd dose; (4) when respondents were offered the 4th dose; and (5) on the day before the survey. Only respondents who had received 2 or more vaccine doses were asked to provide information for the third and fourth time points. For vaccination timeliness, reference dates were primarily sourced from the Oxford dataset, which includes information on vaccination openings or national coverage registers [47].

Building upon the existing concept of social contact matrices used as proxies for potential transmission events [48], we defined the number of age-specific in-person contacts as the number of different individuals with whom the respondent had a direct contact on the day prior to the survey, including an exchange of at least a few words or physical contact (including a handshake, embracing, kissing, contact sports). Expanding this definition, we also introduced a new measure to proxy information diffusion events, namely "discussion contacts," assuming these may significantly influence respondents' opinions and subsequent behavior. Discussion contacts were defined as the number of different individuals with whom respondents had a relevant conversation—whether in person, by phone, or online—during the week preceding the survey. Relevant conversations involved an exchange of information that could help respondents form an opinion on a topic, from personal life choices (eg, relationships, educational choices, work choices, and health choices, including vaccine choices) to general topics (eg, current events, politics, and health, including conversations about vaccines). Both in-person and discussion contacts were stratified by the social group of the contacted individuals, including partner, close family members, other cohabitants, friends, co-workers/classmates, or other acquaintances. All individual-level behavioral, sociodemographic, health, social, and vaccination variables were obtained through respondents' self-reporting in the online questionnaire.

Data Collection

The questionnaire was programmed in Qualtrics, translated into the 5 non-English study languages, and administered online. Data were collected between March 22 and July 30, 2024, in France, Germany, Hungary, Italy, Spain, and the United Kingdom. All survey questions were mandatory; however, "I do not know" and "I prefer not to answer" options were provided for sensitive questions, for example, those related to economic status or personal health.

Data Diagnostics

To minimize fraudulent responses, we removed automated and duplicate records (Table S3 and Figure S1 in Multimedia Appendix 1). Moreover, after data collection, we filtered out additional records deemed unreliable according to standard criteria and flagged inconsistencies affecting specific sections of the survey (Figure 1C, Table S3 and Figure S1 in Multimedia Appendix 1). Flagged responses were excluded from different analysis sections only if they affected the variables under study. To assess whether the data quality filtering procedure disproportionately affected specific sociodemographic groups, we compared the age group, sex, educational attainment, and geographical area of respondents retained in the final analytical sample with those excluded after applying the predefined data quality filters.

Missing data could arise from questionnaire skip logic and "I do not know" or "I prefer not to answer" responses. No imputation was performed. Each analysis included only respondents with valid, nonmissing data for the variables required for that analysis. The frequency of missing data by variable and country is provided in Table S4 in Multimedia Appendix 1.

Likert-scale questionnaire items included in cross-item comparisons were first coded on their original Likert scale, preserving the neutral midpoint for 7-point items, and then linearly rescaled to a common 0-1 range using minimum-maximum normalization. This allowed direct comparison of items measured on 5- and 7-point scales while avoiding artificial collapsing of response categories. In agreement with previous work [49], the daily number of contacts was capped at 30 to limit the influence of outliers. Sensitivity analyses were conducted using alternative cutoffs of 50 and 80 daily contacts to assess the robustness of the findings.

Analytic Strategy

We performed descriptive analyses to investigate willingness to vaccinate, vaccine uptake, perceived severity, relation across COM-B domains, and contact patterns. We computed percentages of respondents by vaccine dose number and willingness level and by combinations of willingness and perceived COVID-19 severity over time. We defined delays in vaccine uptake as the number of months between the country-specific time point when the first dose was offered to each age group and the self-reported vaccination date for each respondent. We computed average delays and corresponding

95% CIs using 500 bootstrap replicates for each willingness and age group. Similarly, contact patterns were summarized using averages and bootstrapped CIs (95% CI).

Respondents were categorized as having high willingness if they rated their willingness to vaccinate as "Very" or "Extremely" and low willingness if they selected "Not very" or "Not at all." Average scores for selected COM-B domains were derived from Likert-scale responses, which were treated as continuous variables, while distinguishing between vaccinated (at least one dose of COVID-19 vaccine ever) and unvaccinated respondents. To provide a more rigorous assessment of differences in behavioral indicators between vaccinated and unvaccinated respondents, we compared the distributions of each Likert-scale item between the 2 groups using 2-sided Wilcoxon rank-sum tests, with statistical significance set at $P<.001$. Tests were performed on unweighted individual-level observations. Poststratification weighting adjustments based on age group (18-29, 30-59, and ≥60 years old), sex (female or male), and NUTS level-1 were applied to correct post–data collection discrepancies with the national population [50]. Weights were applied in the calculation of means and percentage quantities to ensure the survey results accurately reflected the population of interest. Sampling uncertainty around weighted percentage estimates was quantified using approximate 95% CIs based on the Kish effective sample size. Statistical analyses were performed using Python (version 3.11.15; Python Software Foundation).

Proof-of-Concept for Data Integration Into a Behavioral-Epidemic Model

To illustrate how the proposed framework can inform coupled behavioral-epidemic models, we developed a deterministic compartmental transmission model parameterized using behavioral measurements collected through the survey (Figure 1D). The model represents the progression of individuals through epidemiological states (susceptible, infected, recovered, and vaccinated) while accounting for differences in vaccination willingness. Susceptible individuals were stratified into 2 willingness groups corresponding to the extremes of the willingness spectrum assessed in the survey. Vaccination processes were parameterized using vaccine timeliness and declared uptake. Temporal variation in willingness was represented through transitions between the 2 willingness states mediated by epidemic conditions. Increasing infection prevalence promoted transitions toward high willingness, while the accumulation of recovered individuals promoted the reverse transition. The full model equations and parameter definitions are provided in Multimedia Appendix 1.

Ethical Considerations

This study was approved by the Ethics Review Board of Bocconi University in Milan on December 23, 2022, for Italy, France, and Germany (Protocol No. FA000544). Two amendments to the original proposal were subsequently approved to include cognitive interviews in the questionnaire validation procedures (Protocol No. FA000544-01; approval on June 21, 2023) and to add Hungary, Spain and the United Kingdom as additional study locations (Protocol No. EA000682; approval on October 30, 2023). Consent to participation was collected through an online form at the start of the survey. Survey data were collected and stored in compliance with the General Data Protection Regulation (GDPR) and the university's data protection policies. Following data collection, the datasets were anonymized and stored on secure, password-protected servers. For respondents who voluntarily consented to future recontact or provided social media user handles, these identifying details were stored separately from the anonymized research data. Access to the datasets was restricted to authorized research staff. All results are reported in aggregate form to ensure respondent confidentiality. Respondents could withdraw at any time. Those who submitted a complete response received a preagreed compensation through the survey company (€<5; €1=US $1.0926 as of March 11, 2024). No images or other materials included in the manuscript or Multimedia Appendix 1 contain information that could enable identification of individual respondents.

Results

Study Population

We collected 30,429 survey responses across the 6 countries. After applying predefined filters for data quality (Table S3 in Multimedia Appendix 1), we excluded 5172 fraudulent and 3029 implausible responses, retaining 22,228 records for analysis (France n=3627; Germany n=3890; Hungary n=3529; Italy n=4196; Spain n=3686; United Kingdom n=3300; Figure S1 in Multimedia Appendix 1). Comparison of the sociodemographic characteristics of included and excluded respondents showed no major differences between the 2 groups (Table S5 in Multimedia Appendix 1), indicating that the applied data quality filters were unlikely to have introduced substantial selection bias. Among the retained records, we flagged those with inconsistencies in COVID-19 infection or vaccination dates (n=1141), in-person contact numbers (n=7214), and discussion contact numbers (n=8686), as well as records with implausible school attendance on Sundays (n=160) or decimal or negative values where these were not applicable (n=61). We also flagged respondents who received the Johnson & Johnson vaccine, which follows a single-dose schedule that differs from the multidose regimens of other vaccines included in the survey (n=50). The country-specific representativeness of the study populations and respondents' baseline characteristics are reported in Tables S6 and S7 in Multimedia Appendix 1, respectively. To enable cross-country comparisons, responses related to educational levels, geographical distribution, politics, religion, and income were mapped to standardized categories.

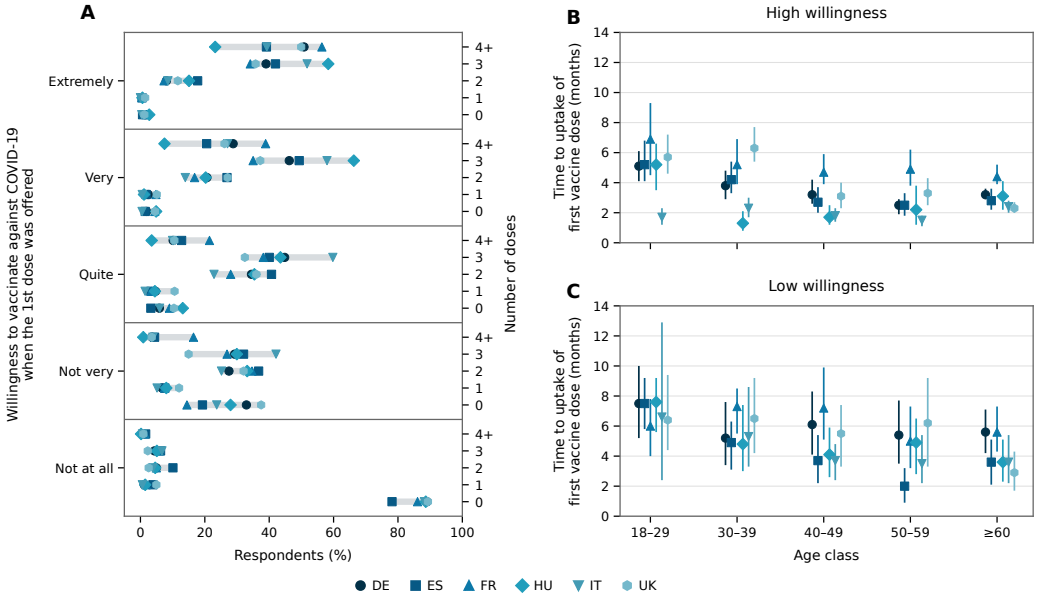
Quantifying the Gap Between Willingness to Vaccinate and Actual Vaccine Uptake

The proportion of respondents who received at least one dose of COVID-19 vaccine exceeded 70% in Germany, Spain, Italy, and the United Kingdom (range: 73.4%, 95% CI 71.4%-75.3% in Germany; 86%, 95% CI 84.4%-87.7% in

Spain), while notably lower uptake was observed in France (64.6%, 95% CI 62%-67.1%) and Hungary (55.1%, 95% CI 52.7%-57.5%; Table S8 in Multimedia Appendix 1). The uptake of COVID-19 vaccine doses correlated positively with influenza vaccination history (Spearman ρ=0.38; range: 0.25, 95% CI 0.22-0.28 in Hungary; 0.49, 95% CI 0.46-0.51 in the United Kingdom) and, to a lesser extent, with self-reported adherence to other protective behaviors at the time of the survey (Figure S2 in Multimedia Appendix 1).

To empirically validate psychological antecedents as proxies for actual behavior, we charted data on respondents' stated willingness to get vaccinated against COVID-19 when the first/second dose was offered to them and their vaccine uptake status at the time of data collection (Figure 2A). In all countries, the proportion of survey respondents taking up to 1, 2, 3, or ≥4 COVID-19 vaccine doses increased with respondents' initial willingness to get vaccinated (Figure 2A; Table S8 in Multimedia Appendix 1). The proportion of unvaccinated respondents was highest among those who initially reported no willingness to get vaccinated (range: 78.2%, 95% CI 72.6%-83.7% in Spain; 89.3%, 95% CI 85.9%-92.7% in the United Kingdom) and lowest among the "extremely willing" (range: 0.4%, 95% CI 0%-1.1% in Italy; 2.7%, 95% CI 0.3%-5.1% in Hungary; Table S8 in Multimedia Appendix 1). Nonetheless, a nonnegligible percentage of respondents in the "not at all willing" group took up ≥2 doses (range: 5.7%, 95% CI 3.2%-8.3% in the United Kingdom; 17.9%, 95% CI 12.8%-23.1% in Spain). Moreover, after excluding respondents whose vaccination decisions were shaped by nonbehavioral factors (see the Figure 2 caption), a notable percentage of respondents who were initially extremely willing to get vaccinated stopped vaccinating after the first or second dose (range: 7.7%, 95% CI 3.6%-11.9% in France; 18.3%, 95% CI 14.3%-22.3% in Spain).

Figure 2. Willingness-behavior gap and timeliness of COVID-19 vaccine uptake. (A) Percentage of respondents taking up 0, 1, 2, 3, or ≥4 doses of the COVID-19 vaccine by country and stated willingness to get vaccinated when the first dose was offered to them. The plot excludes respondents who (1) indicated that COVID-19 vaccination was mandatory for them (Germany [DE] n=573; Spain [ES] n=540; France [FR] n=704; Hungary [HU] n=517; Italy [IT] n=637; United Kingdom [UK] n=442); (2) indicated "I wanted the mandatory Covid passport" as a reason for taking up the vaccine (DE n=904 (23.2%), ES n=783 (21.2%), FR n=1436 (39.6%), HU n=638 (18.1%), IT n=1305 (31.1%), United Kingdom n=560 (17%)); (3) selected the response option "other" and specified their main reason for vaccination in a free-text response (DE n=164; ES n=59; FR n=42; HU n=107; IT n=102; United Kingdom n=48); (4) reported a medical contraindication to vaccination (DE n=15; ES n=4; FR n=12; HU n=24; IT n=15; United Kingdom n=2); (5) stopped vaccinating because they experienced COVID-19 illness (DE n=526; ES n=243; FR n=479; HU n=140; IT n=646; United Kingdom n=203). Among respondents included in this figure, those who were administered 1 (n=21), 2 (n=21), or 3 (n=5) Johnson & Johnson vaccine doses were recoded as having received a total of 2, 3, or 4 doses, respectively. (B) Average number of months between the time point (MM/YYYY) when the COVID-19 vaccine was first offered to each specific age group and when vaccinated respondents in that group received their first dose, by country. The panel includes respondents who were "very" or "extremely" willing to get vaccinated when the first dose was offered to them. Vertical bars indicate 95% bootstrap-based CIs. (C) As in panel B for those who indicated they were "not very" or "not at all" willing to get vaccinated. In panels B and C, the weights reflect 10-year age groups, as shown in the plots, along with sex. Panels B and C exclude respondents who (1); (2); (3) as in A; (4) indicated uptake dates preceding the vaccine offer to their age category (DE n=574; ES n=835; FR n=447; HU n=430; IT n=901; United Kingdom n=683); (5) were administered the Johnson & Johnson vaccine, which was offered to the population with a delay (DE n=11; ES n=8; FR n=6; HU n=17; IT n=6; United Kingdom n=2). In all panels, countries are distinguished by color and marker: Germany (DE; circle), Spain (ES; square), France (FR; upward triangle), Hungary (HU; diamond), Italy (IT; downward triangle), and the United Kingdom (UK; hexagon).



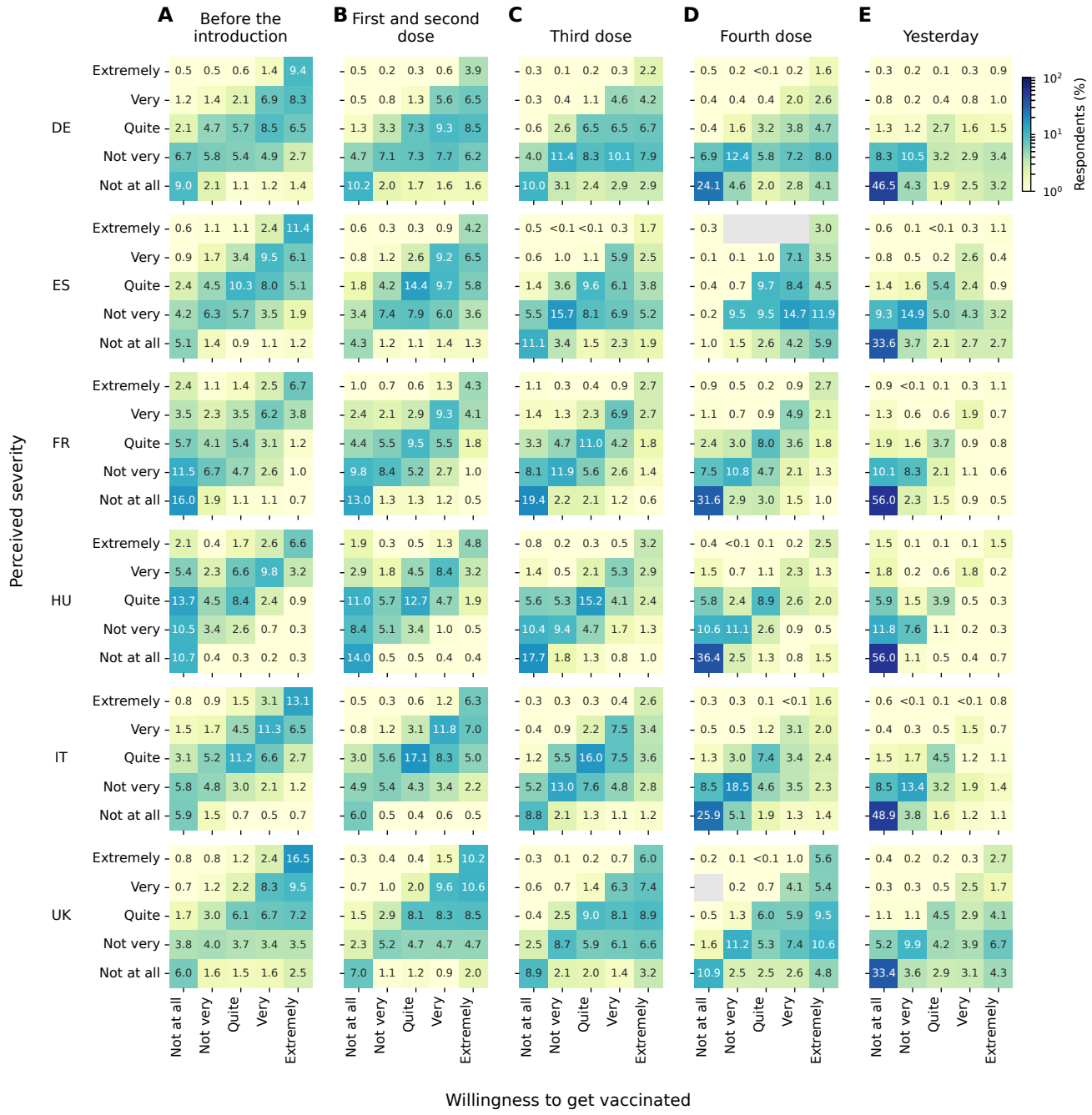
We investigated age-specific vaccination timeliness according to respondents' initial willingness to vaccinate (Figure 2B and 2C; Table S9 in Multimedia Appendix 1). On average, respondents aged 18-29 years took 5.6 (95% CI 5.1-6.1) months to receive their first dose after the vaccine was made available to their age group (delay range: 3, 95% CI 2.1-4 months in Italy; 6.6, 95% CI 5.5-7.6 months in Hungary). In comparison, older adults aged ≥60 years received the vaccine on average within 3.3 (95% CI 3-3.5) months of its availability to their age group (delay range: 2.5, 95% CI 2-2.9 months in the United Kingdom; 4.7, 95% CI 4.1-5.2 months in France).

In all countries, vaccination timeliness increased with initial willingness to get vaccinated. Those with high initial willingness received their first dose on average within 3.2 (95% CI 3-3.4) months (delay range: 2, 95% CI 1.7-2.2 months in Italy; 5, 95% CI 4.6-5.7 months in France; Figure 2B; Table S9 in Multimedia Appendix 1). In comparison, those with low initial willingness delayed their first dose by 2 additional months on average (5.3, 95% CI 5-5.8; delay range: 4.1, 95% CI 3.6-5.1 months in Italy; 6.2, 95% CI 5.6-6.9 months in France; Figure 2C; Table S9 in Multimedia Appendix 1).

Retrospective Assessment of Temporal and Country-Specific Variation of Behavioral Factors

We investigated respondents' retrospective reports of perceived COVID-19 severity and willingness to vaccinate against COVID-19 across 5 time points and 6 countries. Before the vaccine was introduced (Figure 3A), the percentage of respondents reporting high or extremely high levels of perceived COVID-19 severity ranged from 32.4% (95% CI 30.8%-33.9%) in Germany to 44.9% (95% CI 43.3%-46.6%) in Italy. Willingness to vaccinate against COVID-19 showed a greater variation across countries, with the percentage of respondents reporting high or extreme willingness to vaccinate against COVID-19 ranging from 27% (95% CI 25.3%-28.7%) in Hungary to 61.7% (95% CI 60%-63.4%) in the United Kingdom. At the same time point, a considerable percentage of respondents reported they were not at all willing to get vaccinated, both in France (39.1%, 95% CI 37.3%-40.8%) and Hungary (42.5%, 95% CI 40.6%-44.4%), while lower values were recorded in all other countries (range: 13%, 95% CI 11.8%-14.2% in the United Kingdom; 19.4%, 95% CI 18.1%-20.7% in Germany).

Figure 3. Temporal and country-specific variation in perceived COVID-19 severity and willingness to vaccinate against COVID-19. Weighted percentages of respondents according to retrospectively reported levels of perceived COVID-19 severity and willingness to vaccinate at 5 predefined time points. (A) Before the introduction of the COVID-19 vaccines. (B) When the first and second vaccine doses were offered to respondents. (C) When the third vaccine dose was offered to respondents. (D) When the fourth vaccine dose was offered to respondents. (E) The day before the survey. Only respondents who received 2 or more vaccine doses were asked to provide information shown in panels C and D. Cell colors range from yellow to dark blue, with darker blue indicating higher percentages of respondents. Gray shading indicates that no respondents were in that specific group. DE: Germany; ES: Spain; FR: France; HU: Hungary; IT: Italy; UK: United Kingdom.



When considering the time when the first vaccine dose was offered to them (Figure 3B), a lower percentage of respondents retrospectively reported high or extremely high perceived COVID-19 severity in all countries (range: 20.2%, 95% CI 18.9%-21.5% in Germany; 36.8%, 95% CI 35.1%-38.5% in the United Kingdom). At that time point, the proportion of those reporting high or extremely high willingness to vaccinate was similar in all populations to that reported before vaccine rollout (range: 26.7%, 95% CI 25%-28.3% in Hungary; 61%, 95% CI 59.3%-62.8% in the United Kingdom). Among respondents who had received 2 or more doses, retrospective reports indicated progressively lower perceived severity and willingness to get additional COVID-19 vaccine doses as the vaccination campaign progressed (Figures

3C-3D). On the day before the survey (Figure 3E), larger proportions of respondents reported low or no perceived COVID-19 severity (range: 77.3%, 95% CI 75.8%-78.8% in the United Kingdom; 86.9%, 95% CI 85.8%-88% in Germany), and the majority indicated no or low willingness to get vaccinated against the disease (range: 55.5%, 95% CI 53.8%-57.3% in the United Kingdom; 87.6%, 95% CI 86.4%-88.9% in Hungary).

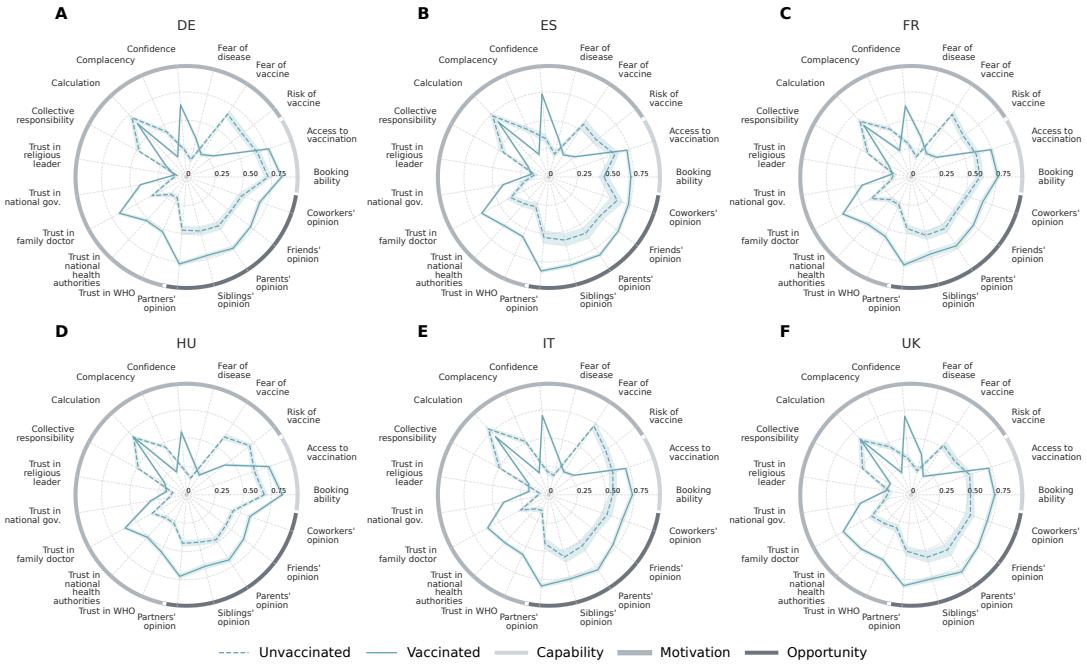
Disentangling Behavioral Mechanisms Across COM-B Domains

Grounding the empirical data collection in a validated behavioral model allowed us to collect abundant information on potential behavioral determinants and to systematically assess complex mechanisms underlying behavioral choices. Responses capturing different elements of the COM components of behavior were compared after stratifying respondents by their COVID-19 vaccination status, with "vaccinated" respondents including anyone who received at least one dose ever.

A comparison of vaccinated and unvaccinated respondents revealed statistically significant differences in the distributions of scores for nearly all behavioral indicators under analysis across all 6 countries, with 96% of comparisons remaining significant at $P<.001$ (Wilcoxon rank-sum tests; Figure S3 in Multimedia Appendix 1). Vaccinated respondents tended to report higher scores for their booking ability, access to vaccination, vaccine confidence, trust in governmental and public health institutions, and perceived support for vaccination within their social environment. Unvaccinated respondents tended to report higher scores for perceived vaccine risk, fear of vaccination, and complacency. The largest between-group differences were consistently observed for behavioral indicators within the motivation domain.

Figure 4 complements these results by presenting the corresponding weighted mean responses and providing a descriptive overview of behavioral profiles of vaccinated and unvaccinated respondents across the COM-B domains. The radar plots illustrate the direction and relative magnitude of the statistically significant between-group differences, showing consistent patterns across all 3 COM-B domains.

Figure 4. Systematic mapping of behavioral factors potentially associated with COVID-19 vaccination behavior. (A) Radar charts showing weighted mean responses to selected survey questions among adult respondents in Germany. We measured questionnaire items on Likert scales across COM-B model domains, stratified by respondents' COVID-19 vaccination status. Vaccinated respondents included those who had received at least one dose of the COVID-19 vaccine ever. Solid (dashed) lines represent weighted mean values across items for vaccinated (unvaccinated) individuals, and shaded areas indicate 95% bootstrap CIs around the mean. The plots include only COM-B variables that were measured on Likert scales and do not represent all variables assessed within each domain. In the opportunity section, responses referred to the social opportunity/peer influence domain and only included those from respondents who had previously reported the presence of each given social group. For this variable, average values showed each social group's level of agreement with the view that vaccines are essential for protecting human health, as reported by respondents. (B-F) As in panel A, for Spain, France, Hungary, Italy, and the United Kingdom, respectively. In all panels, the plots exclude respondents who (1); (2); (3); and (4) as in Figure 2A. Questionnaire items corresponding to the plotted variables are listed in Table S10 in Multimedia Appendix 1. The average values are reported in Table S11 in Multimedia Appendix 1. DE: Germany; ES: Spain; FR: France; HU: Hungary; IT: Italy; UK: United Kingdom.



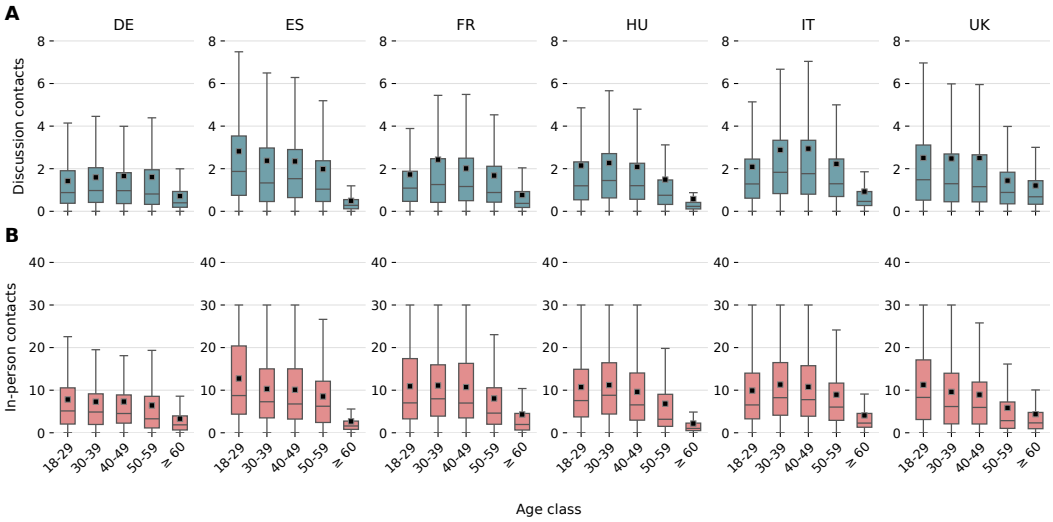
A more granular stratification by the number of COVID-19 vaccine doses received (0, 1-2, and ≥3 doses) yielded the same overall pattern, with respondents who had received 1-2 doses exhibiting intermediate values between those of unvaccinated respondents and those who had received ≥3 doses across COM-B domains (Figure S4 in Multimedia Appendix 1).

Similar, albeit smaller, differences were observed between respondents who reported any influenza vaccination and those who reported none, again most visible in the motivation domain (Figure S5; Table S11 in Multimedia Appendix 1).

Introducing New Behavioral Dimensions for Coupled Behavioral-Epidemic Modeling

To enable the investigation of how peer communication may shape individual opinions and subsequent behaviors, we amplified the well-established quantification of in-person social contacts for infectious disease modeling [48] by complementing it with the new dimension of discussion contacts (Figure 5 and Table S12 in Multimedia Appendix 1).

Figure 5. A novel dimension of social contacts. (A) Number of daily discussion contacts by age group and country among adult respondents. The number of weekly discussion contacts as assessed in the survey was recalculated as daily. Boxes represent medians and interquartile ranges. Small rectangles within each box indicate the mean number of daily contacts in that age group. Whiskers represent minimum and maximum values, capped at 30 daily contacts; values >30 were set to 30. (B) As in A for in-person contacts by age group and country. In both panels, respondents flagged for reporting implausible contact numbers were excluded (DE n=1452; ES n=1725; FR n=1395; HU n=1561; IT n=1780; UK n=1180). DE: Germany; ES: Spain; FR: France; HU: Hungary; IT: Italy; UK: United Kingdom.



Across all countries, older adults aged ≥60 years consistently reported the lowest average number of daily discussion contacts, ranging from 0.5 (95% CI 0.4-0.6) in Spain to 1.2 (95% CI 1-1.4) in the United Kingdom (Figure 5A and Table S12 in Multimedia Appendix 1). Among those aged <60 years, contact patterns varied by country. In Germany, discussion contacts remained relatively stable across age groups, with averages ranging from 1.4 (95% CI 1.2-1.6) among respondents aged 18-29 years to 1.7 (95% CI 1.4-1.9) among those aged 40-49 years. Similarly, in the United Kingdom, the average number of discussion contacts remained consistently high across respondents aged 40-49 years and decreased to 1.4 (95% CI 1.3-1.6) among those aged 50-59 years. In contrast, a progressive decline with age was observed in Spain, where contact numbers dropped from 2.8 (95% CI 2.4-3.2) in those aged 18-29 years to 2 (95% CI 1.7-2.3) among those aged 50-59 years. A distinct pattern emerged in France, Hungary, and Italy, where the average number of discussion contacts peaked among those aged 30-39 years, reaching 2.4 (95% CI 2-2.9) in France, 2.3 (95% CI 2-2.6) in Hungary, and 2.9 (95% CI 2.5-3.2) in Italy.

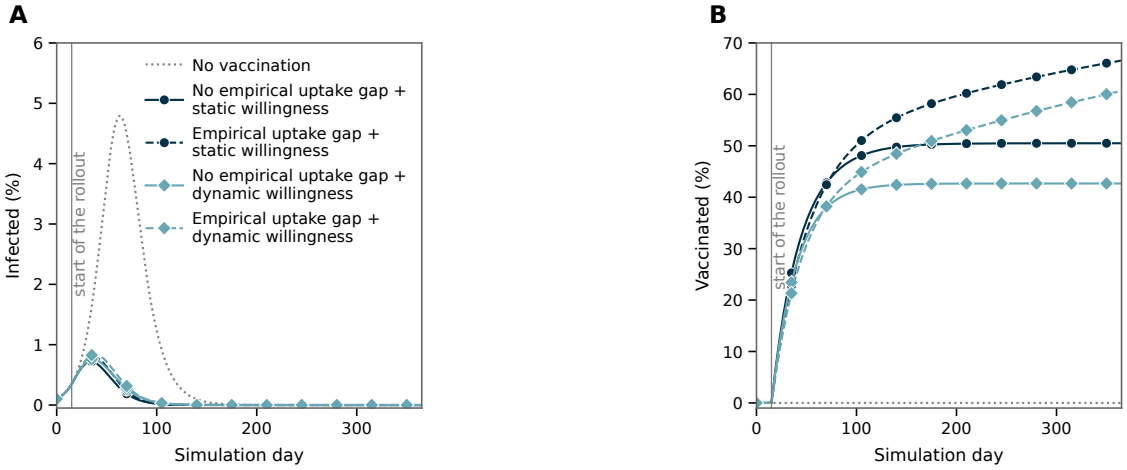
The average number of daily discussion contacts was strongly correlated with in-person contacts (Pearson r=0.93; Figure S6 in Multimedia Appendix 1). In all countries, individuals aged ≥60 years reported the lowest number of in-person contacts, ranging from 2.2 (95% CI 1.7-2.7) in Hungary to 4.4 (95% CI 3.9-4.9) in the United Kingdom (Figure 5B and Table S12 in Multimedia Appendix 1). In Hungary and Italy, the highest levels of in-person contacts were observed among adults aged 30-39 years, with daily averages of 11.2 (95% CI 10.4-12) and 11.3 (95% CI 10.5-12.2), respectively. In contrast, the number of in-person contacts peaked among younger adults aged 18-29 years, at 11.3 (95% CI 10.3-12.2) in the United Kingdom and 12.7 (95% CI 11.8-13.7) in Spain, respectively. Similar average numbers of daily in-person contacts were reported in all age groups <50 years in Germany (range: 7.3, 95% CI 6.5-8.1 among those aged 30-39 years; 7.8, 95% CI 7-8.6 among those aged 18-29 years). Median values and age-specific patterns remained almost unchanged across all countries when varying the cutoff threshold (Figures S7 and S8 in Multimedia Appendix 1). Distinguishing between vaccinated and unvaccinated individuals, no substantial differences in either average daily discussion or in-person contacts were observed at the time of data collection (Figure S9 in Multimedia Appendix 1).

Translating Behavioral Measurements Into a Coupled Behavioral-Epidemic Model

To illustrate one possible pathway through which the proposed framework can inform coupled behavioral-epidemic models, we focused on the 2 behavioral findings that emerged most directly from the survey. We incorporated (1) willingness-dependent differences in vaccination uptake probability and timeliness (Figure 2) and (2) temporal changes in vaccination willingness together with perceived disease severity (Figure 3). The first finding motivated the representation of 2 behavioral states within the susceptible population, each characterized by willingness-specific vaccination rates informed by the survey. The second finding motivated the representation of willingness as a dynamic behavioral process, with transitions between the 2 states (Figure S10 and Table S13 in Multimedia Appendix 1). We progressively introduced these features into the model to isolate their individual and combined contribution to vaccination dynamics. We started from a scenario in which only high willingness individuals vaccinate, and willingness remains fixed throughout the epidemic (no empirical uptake gap and static willingness). We then introduced the empirically observed differences in vaccination uptake probability and timeliness between willingness groups while keeping willingness fixed (empirical uptake gap and static willingness). Next, we allowed willingness to evolve over time through transitions between behavioral states while maintaining vaccination restricted to high willingness individuals (no empirical uptake gap and dynamic willingness). Finally, we combined the 2 empirical features (empirical uptake gap and dynamic willingness). A no-vaccination scenario was included as a baseline for comparison.

Under the assumption of complete vaccine protection, accounting for the empirical uptake gap increased vaccination coverage relative to scenarios where vaccination was restricted to high willingness individuals (Figure 6). Allowing willingness to evolve over time resulted in slower vaccination uptake and lower final coverage than assuming fixed willingness. The results remained robust under lower vaccine effectiveness and different assumptions governing changes in willingness over time (Figures S11-S12 in Multimedia Appendix 1).

Figure 6. Epidemiological outcomes of a coupled behavioral-epidemic model parameterized with the empirical behavioral data collected through the proposed framework. (A) Percentage of infected individuals over time. (B) Vaccination coverage over time. Solid and dashed lines distinguish scenarios without and with the empirical uptake gap, respectively, while blue circle and cyan diamond markers indicate static and dynamic willingness, respectively. The no-vaccination scenario is represented by a dotted line without markers. The vertical gray line indicates the start of the vaccination rollout.



Discussion

In response to growing calls for greater collaboration across scientific fields [18,27,51], we implemented a novel interdisciplinary study to address a longstanding challenge: improving the measurement and representation of the dynamic, multidimensional nature of human behavior in epidemiological approaches to modeling behavior-disease interactions. Acknowledging the limitations of traditional behavioral science methods in generating data that can be readily incorporated into epidemic models [23,27], we systematically integrated expertise from the behavioral and social sciences, epidemiology, and mathematical modeling to design and implement a large-scale, nationally representative survey across 6 European countries. The resulting dataset provides a theory-grounded empirical basis for the development of quantitative measures that better reflect the context-sensitive nature of vaccine intentions, uptake, and delay, thereby enhancing their relevance for epidemic preparedness and response analyses.

A plethora of theories and conceptual approaches dedicated to investigating the multifaceted nuances of human behavior is available, and published reviews can help navigate this landscape [32]. Using an explicit behavioral theory provides a systematic structure for identifying and

investigating relevant influences on behavioral responses to infectious disease, rather than relying on an ad hoc selection of factors and assumed relationships [28,52]. We found the COM-B model to be particularly well suited to our purpose, as it helped differentiate conceptually related behavioral constructs, such as risk perception and fear, while retaining sufficient flexibility to adapt the survey tool to our specific research objectives [28].

Within this conceptual framing, we quantified the gap between willingness to vaccinate and actual vaccine uptake, providing empirical evidence to refine the use of psychological antecedents as proxies for actual behavior to inform epidemic scenarios. Our findings aligned with the psychological literature [53-56], indicating that intentions alone rarely provide a complete explanation for human behavior [29,56]. This was also corroborated by other survey findings during the COVID-19 pandemic, where vaccine uptake [57] and timeliness [58,59] did not always align with respondents' positive intentions. Accordingly, the uptake of sequential vaccine doses was negatively affected by adverse experiences with the first dose [60] and growing vaccination fatigue [61,62].

To our knowledge, the level of granularity and internal consistency with which the intention-behavior gap can be examined in our data is unprecedented and represents a distinctive contribution of this work. Our data allow for a detailed examination of COVID-19 vaccine uptake by dose number and an empirical quantification of delays between official recommendations and actual vaccination. These empirically documented nuances in the intention-behavior gap, including dose-specific uptake and delays in vaccination, may have critical implications for policy planning and effectiveness, because analyses relying on psychological antecedents alone may misestimate the timing or magnitude of epidemic waves, with implications for the design, timing, and evaluation of public health interventions and policies, including vaccination campaigns.

By examining respondents' retrospective reports of perceived COVID-19 severity and vaccine willingness across critical phases of the vaccine rollout, we identified substantial differences across time points and countries, reflecting context-sensitive behavioral heterogeneity. The temporal patterns observed in these reports are also consistent with fluctuations in perceived COVID-19 severity and willingness to vaccinate documented in multi-wave survey initiatives conducted across Europe either concurrently or prior to our study [63-65], with hesitant individuals exhibiting the greatest variability over time [65]. Previous studies suggested that such variations may reflect infection rates [66,67], sociodemographic attributes [68], and vaccination status [69]. Our dataset offered the opportunity to examine the relationship between these 2 variables using parallel rating scales within the same sample. Such high-resolution empirical data incorporating behavioral measures across multiple countries and retrospective time points can significantly reduce assumptions that fail to account for changes in public responses to health threats [70,71].

Using the COM-B model, we identified distinct behavioral profiles associated with vaccination status. Key differentiators emerged in the motivation domain and included fear of side effects, perceived risk, vaccine confidence, and trust in family doctors, suggesting socially patterned differences in perceptions of risk, trust, and responsibility. These results align with findings from previous surveys conducted in Europe. Fear of side effects and concerns about the rapid vaccine development were the most commonly reported reasons for vaccine refusal or delay in Italy [58], while low perceived risk of COVID-19 and distrust in health authorities were associated with low vaccination willingness or uptake in France [72], England [73], and other European countries [64,65]. In the United Kingdom, vaccinated respondents exhibited higher confidence in vaccine safety, likely due to selective information exposure [74]. Trust in family doctors and experts also emerged as a strong positive predictor of uptake in France [72], consistent with previous findings from Hong Kong and Singapore [75]. Conversely, differences in the opportunity domain appeared to be less pronounced between vaccinated and unvaccinated individuals, both in terms of average opinion toward vaccination in selected social groups and average number of discussion contacts. This could suggest that behavioral homophily—while evidently present—may not be the dominant driver of observed differences across vaccination statuses. Vaccine uptake also correlated with other behaviors in our study population, in line with United Kingdom data from 2021, where respondents who received 2 doses of the COVID-19 vaccine were more likely to resume social activities, and those with greater motivation, opportunity, and capability continued engaging in preventive measures such as mask-wearing and distancing [76].

Together, these findings underscore the importance of examining the full range of behavioral domains in an integrated manner rather than in isolation, as varying combinations of social and cognitive factors may lead to distinct patterns of compliance with protective measures. The overall effect of the epidemic response may depend on the interconnection of individual adherence decisions [77]. Nevertheless, most epidemiological modeling approaches accounting for behavioral mechanisms overlook complex social interactions, such as the peer-driven formation and diffusion of opinions [19,20,40,78]. We found that the distribution of discussion contacts closely mirrored that of in-person contacts in the same country, indicating that discussion interactions may represent a small-scale projection of broader social interactions. By accounting for mechanisms such as contact heterogeneity, peer influence, and social learning—and for how these social interactions shape disease spread—public health analyses can better reflect the complexity of real-world dynamics and help avoid misinterpretations that undermine epidemic response efforts [79].

To exemplify how the collected behavioral measurements can be translated into models, we developed a behavioral-epidemic transmission model, built around 2 empirical observations emerging from the survey. First, vaccination willingness and vaccination uptake were distinct, with many willing individuals delaying or not receiving vaccination. Second,

willingness was dynamic and changed alongside perceived disease severity. Accordingly, we represented willingness as a dynamic behavioral state that conditions vaccination uptake. Consistent with previous behavioral-epidemic models [21,22,80,81], epidemic conditions were assumed to shape perceived risk. In our survey, changes in perceived risk coincided with changes in willingness. To preserve the behavioral pathway from intention to behavior suggested by the empirical data, we allowed epidemic conditions to influence vaccination uptake indirectly through changes in willingness. Incorporating both the empirical gap between willingness and uptake and dynamic willingness transitions produced vaccination trajectories that differed from those obtained when either mechanism was considered in isolation, illustrating that both behavioral processes contribute to vaccination dynamics. The model also accommodates further extensions, including the explicit representation of individuals who never enter the vaccination pathway, as suggested by our empirical findings. More generally, these results show that translating behavioral data into epidemic models can inform not only model parameterization but also model structure, including the selection of behavioral states and processes with consequences for vaccination dynamics.

Several limitations must be acknowledged. First, the retrospective, self-reported nature of behavioral and cognitive data—particularly across multiple time points—may introduce recall bias [82]. To mitigate this risk, we used memory aids, such as visual timelines, and anchored questions to respondents' lived experiences to help them identify relevant time frames. For instance, perceived COVID-19 severity was assessed for time points chosen to correspond to key milestones of each country's vaccination campaign. In addition, retrospective assessments of willingness to receive the COVID-19 vaccine and of perceived COVID-19 severity may have been affected by hindsight bias [83], whereby respondents' recollection of past attitudes and perceptions is influenced by subsequent experiences and knowledge. Nonetheless, the retrospective responses showed coherent patterns across countries and were consistent with respondents' reported vaccination behavior, providing some reassurance that the retrospective measures captured meaningful differences despite the potential for recall and hindsight bias. Despite its limitations, the retrospective design enabled analyses across time and contexts, including complex constructs such as the intention-behavior gap—otherwise requiring resource-intensive longitudinal studies. Second, the use of online survey panels may pose risks of selection bias [84], impacting both the representativeness of the sample and the validity of the responses. To address this concern, nationally representative quotas were established based on key demographic variables, and recruitment was adjusted in real time to ensure these quotas were achieved. Comparison of vaccine coverage and sociodemographic variables with national statistics and similar surveys [85] did not reveal major recall or selection biases. Third, individuals under the age of 18 years were excluded from this study. Using the age of majority as the inclusion criterion ensured a consistent recruitment strategy across countries with different legal and ethical frameworks governing the participation of minors in research [86,87], as well as different requirements and practices regarding adolescents' involvement in medical decision-making [88]. Nevertheless, older adolescents, in particular, may have played an active role in decisions regarding COVID-19 vaccination [89]. Thus, our study did not capture a segment of the population that may have differed from adults in both COVID-19 vaccination uptake and the behavioral determinants underlying vaccination decisions. This limitation did not apply to younger children, who were represented indirectly through their caregivers. Respondents who were parents of at least one child aged <10 years were asked to report their children's vaccination status for both COVID-19 and routine childhood immunizations, as well as the reasons underlying their acceptance or refusal of COVID-19 vaccination for their children. Fourth, the exact form and strength of the epidemic-driven behavioral feedback introduced in the coupled behavioral-epidemic model remain to be estimated through longitudinal behavioral data and formal model calibration. Finally, although the findings of this study may not be generalizable beyond Europe or the COVID-19 pandemic, the methodological approach itself is transferable to other contexts and settings. Indeed, what we have shown is a structured process for integrating validated behavioral theory with epidemic modeling requirements. This has led us to define measurable behavioral constructs and corresponding survey instruments, while allowing adaptation to different cultural and epidemiological contexts and to the study of different preventive health behaviors. Wider adoption of this type of design will depend on continued investment in interdisciplinary collaborations dedicated to the gathering of complex behavioral data to complement epidemic modeling tools. Emerging efforts to strengthen pandemic preparedness and public health decision-making increasingly emphasize the need for a deeper, empirically grounded understanding of how individuals and communities perceive risk, form intentions, and translate these into action across changing contexts [3,6]. Concurrently, there is growing recognition that such insights must be supported by robust quantitative approaches capable of measuring these behavioral processes in ways that are both realistic and applicable [2,27,90].

Despite the recent surge in interdisciplinary research at the intersection of infectious disease epidemiology and behavioral science prompted by the influenza and COVID-19 pandemics, truly integrative advances remain limited [21,22,51]. This work provides a robust empirical foundation for a new generation of theory-informed, data-driven quantitative approaches that better reflect behavioral complexity, improve disease trend forecasting, and strengthen policy relevance. Though cross-sectional by design, our dataset offers a robust combination of behavioral depth, theoretical coherence, and population-level representativeness. Our theory-informed design supports both rigor and reproducibility, extending past efforts [91] to systematize behavioral integration into epidemic modeling for preparedness and response.

Looking ahead, longitudinal frameworks for collecting [92,93] and sharing [94] behavioral data would substantially

increase their applicability for quantitative analyses of behavioral trajectories over time. In health crisis contexts, where time and resources are constrained, pre-established data systems become essential [95-97]. Embedding behavioral modules into participatory surveillance platforms offers a promising solution [98-100].

Equally important is the integration of different data sources. Triangulating survey responses with observational data from separate sources can help assess their reliability and mitigate systematic biases [92,101,102]. Given the increasingly intertwined nature of human behavior across on- and offline environments, emerging data streams, such as those from social media or personal digital devices, offer valuable opportunities to capture high-resolution, passively collected behavioral indicators [2,103]. For instance, a number of respondents in our survey provided access to their social media content. The publicly available information on their profiles, such as the content of posts, comments, and messages shared publicly or on open groups, websites followed, or "likes," will allow us to connect and cross-validate information from both the physical and digital realms. Finally, novel modeling approaches that incorporate AI [104,105] further underscore the need for rich, high-resolution behavioral training datasets to simulate human decision-making and behavioral dynamics.

In conclusion, this study shows how sustained interdisciplinary collaboration can be embedded throughout the research process to generate behavioral evidence that is both theoretically grounded and directly relevant to epidemic modeling. Building on interdisciplinary initiatives already emerging at the national [106,107] and international levels [108,109], our study puts this approach into practice, moving beyond conventional behavioral data collection by explicitly linking behavioral measurement to epidemic modeling requirements. Effective integration requires a shared conceptual and methodological language, as well as a high degree of flexibility and compromise to better account for behavioral heterogeneity and change. Embedding such approaches within longitudinal and integrated data infrastructures could strengthen the evidence available for epidemic preparedness, scenario development, and the design and evaluation of public responses.

Acknowledgments

We acknowledge precious input for both the conceptualization of the scientific approach and the development of the survey tool from Delia Baldassarri, Alain Barrat, Chris Bauch, Simon Cauchemez, Laura Di Domenico, Anthony Hauser, Sune Lehmann, Anna Sára Ligeti, Susan Michie, Saad Omer, Daniela Paolotti, Nicola Perra, Daniela Perrotta, Piero Poletti, Renu Singh, Ádám Stefkovics, Emilio Zagheni, Alfonso de Miguel, and Carlos Gracia. We thank researchers from the Dondena Centre at Bocconi University for providing feedback on the survey tool. We thank the Dondena Centre for hosting the research project IMMUNE and for providing continuous support.

Generative AI Use

The authors declare the use of generative AI (GenAI) in the research and writing process. According to the GAIDeT taxonomy (2025), the following tasks were delegated to GenAI tools under full human supervision:
Literature search and systematization
Code optimization
Process automation
Text generation
Proofreading and editing
Summarizing text
The GenAI tool used was: ChatGPT 5.5. Responsibility for the final manuscript lies entirely with the authors. GenAI tools are not listed as authors and do not bear responsibility for the final outcomes. Declaration submitted by all authors.

Funding

Surveys in France, Germany, Italy, and the United Kingdom were funded by the European Research Council (ERC) Consolidator Grant "IMMUNE" (ID: 101003183). Additional support was provided by the Piano Nazionale di Ripresa e Resilienza (PNRR) Grant BEHAVE-MOD (ID: SA-02.P0001), and by the Health Emergencies Analytics Lab (HEAL), supported by the "Fondazione Romeo ed Enrica Invernizzi." The survey in Spain was funded by the Complex Systems & Networks Lab (COSNET), Institute for Biocomputation and Physics of Complex Systems (BIFI). The survey in Hungary was funded by the National Laboratory for Health Security (RRF-2.3.1-21-2022-00006).
VC acknowledges support from the Agence Nationale de la Recherche (ANR) Grant DATAREDUX (ANR-19-CE46-0008-03) and the European Union Horizon Europe Grant ESCAPE (101095619).
YM and AA were partially supported by the Government of Aragón, Spain, and "European Regional Development Fund (ERDF) A way of making Europe" through Grant No. E36-26R (FENOL) and by Grant No. PID2023-149409NB-I00 funded by Ministerio de Ciencia, Innovación y Universidades/ Agencia Estatal de Investigación (MICIU/AEI/10.13039/501100011033). AA acknowledges support from the Grant No. RYC2021-033226-I funded by Ministerio de Ciencia, Innovación y Universidades/ Agencia Estatal de Investigación (MICIU/AEI/10.13039/501100011033) and the European Union NextGenerationEU/ Plan de Recuperación, Transformación y Resiliencia (PRTR).

LPL acknowledges support from Nuffield College, Clarendon Fund, and the International Max Planck Research School for Population, Health and Data Science (IMPRS-PHDS). MK acknowledges support from the BEQUAL NKFI-ADVANCED Grant No. 153172 and the National Laboratory for Health Security (RRF-2.3.1-21-2022-00006).
The funders had no involvement in the study design, data collection, analysis, interpretation, or the writing of the manuscript.

Data Availability

The anonymized data underlying the analyses presented in this study will be made openly available in a public data repository in June 2027. Until then, the data are available upon reasonable request for scientific research purposes. For further information or to request access to the full dataset, please contact the corresponding author.

Authors' Contributions

AM conceived the study and led the research project. AM, MC, LL, LPL, and VO conceptualized and developed the questionnaire, with inputs from CC and DB. FT, JK, MK, PM, VC, AA, and YM provided domain expertise throughout study design, data collection, and quality control. LL and LPL led the implementation of the survey. LL, LPL, and CC ensured data quality. LL, LPL, CC, EDA, and FB conducted data cleaning. EC conducted the analysis and produced the visualizations. AM, VO, and EC conceptualized and wrote the manuscript. All authors interpreted the results, reviewed, and approved the final version of the manuscript.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Supplementary tables, figures, and methods detailing survey measures, data quality procedures, sample characteristics, numerical data underlying the main article's plots, additional analyses, coupled behavioral-epidemic model specifications, and sensitivity analyses.
[PDF File (Adobe File), 13826 KB-Multimedia Appendix 1]

Multimedia Appendix 2

IMMUNE behavioural questionnaire.
[DOCX File (Microsoft Word File), 279 KB-Multimedia Appendix 2]

References

1. Fattahi H, Seproo FG, Fattahi A. Effective factors in people's preventive behaviors during COVID-19 pandemic: a systematic review and meta-synthesis. BMC Public Health. Jun 18, 2022;22(1):1218. [doi: 10.1186/s12889-022-13621-y] [Medline: 35717144]
2. Buckee C, Noor A, Sattenspiel L. Thinking clearly about social aspects of infectious disease transmission. Nature. Jul 2021;595(7866):205-213. [doi: 10.1038/s41586-021-03694-x] [Medline: 34194045]
3. Michie S, West R. Sustained behavior change is key to preventing and tackling future pandemics. Nat Med. May 2021;27(5):749-752. [doi: 10.1038/s41591-021-01345-2] [Medline: 33972794]
4. Rahmandad H, Xu R, Ghaffarzadegan N. A missing behavioural feedback in COVID-19 models is the key to several puzzles. BMJ Glob Health. Oct 2022;7(10):e010463. [doi: 10.1136/bmjgh-2022-010463] [Medline: 36283733]
5. How modelling can better support public health policy making: the Lancet Commission on Strengthening the Use of Epidemiological Modelling of Emerging and Pandemic Infectious Diseases. The Lancet. Mar 2024;403(10429):789-791. [doi: 10.1016/S0140-6736(23)02758-7]
6. Van Bavel JJ, Baicker K, Boggio PS, et al. Using social and behavioural science to support COVID-19 pandemic response. Nat Hum Behav. May 2020;4(5):460-471. [doi: 10.1038/s41562-020-0884-z] [Medline: 32355299]
7. Yan Y, Malik AA, Bayham J, Fenichel EP, Couzens C, Omer SB. Measuring voluntary and policy-induced social distancing behavior during the COVID-19 pandemic. Proc Natl Acad Sci U S A. Apr 20, 2021;118(16):e2008814118. [doi: 10.1073/pnas.2008814118] [Medline: 33820846]
8. Fenichel EP, Castillo-Chavez C, Ceddia MG, et al. Adaptive human behavior in epidemiological models. Proc Natl Acad Sci U S A. Apr 12, 2011;108(15):6306-6311. [doi: 10.1073/pnas.1011250108] [Medline: 21444809]
9. Bauch CT. Imitation dynamics predict vaccinating behaviour. Proc Biol Sci. Aug 22, 2005;272(1573):1669-1675. [doi: 10.1098/rspb.2005.3153] [Medline: 16087421]
10. Saad-Roy CM, Traulsen A. Dynamics in a behavioral-epidemiological model for individual adherence to a nonpharmaceutical intervention. Proc Natl Acad Sci U S A. Oct 31, 2023;120(44):e2311584120. [doi: 10.1073/pnas.2311584120] [Medline: 37889930]

11. De Gaetano A, Barrat A, Paolotti D. Modeling the interplay between disease spread, behaviors, and disease perception with a data-driven approach. Math Biosci. Dec 2024;378:109337. [doi: 10.1016/j.mbs.2024.109337] [Medline: 39510244]
12. Perra N, Balcan D, Gonçalves B, Vespignani A. Towards a characterization of behavior-disease models. PLoS ONE. 2011;6(8):e23084. [doi: 10.1371/journal.pone.0023084] [Medline: 21826228]
13. Funk S, Gilad E, Watkins C, Jansen VAA. The spread of awareness and its impact on epidemic outbreaks. Proc Natl Acad Sci U S A. Apr 21, 2009;106(16):6872-6877. [doi: 10.1073/pnas.0810762106] [Medline: 19332788]
14. Wang Z, Bauch CT, Bhattacharyya S, et al. Statistical physics of vaccination. Phys Rep. Dec 2016;664:1-113. [doi: 10.1016/j.physrep.2016.10.006]
15. Verelst F, Willem L, Beutels P. Behavioural change models for infectious disease transmission: a systematic review (2010-2015). J R Soc Interface. Dec 2016;13(125):20160820. [doi: 10.1098/rsif.2016.0820] [Medline: 28003528]
16. Weston D, Hauck K, Amlôt R. Infection prevention behaviour and infectious disease modelling: a review of the literature and recommendations for the future. BMC Public Health. Mar 9, 2018;18(1):336. [doi: 10.1186/s12889-018-5223-1] [Medline: 29523125]
17. Manfredi P, D'Onofrio A. Modeling the Interplay Between Human Behavior and the Spread of Infectious Diseases. Springer; 2013. [doi: 10.1007/978-1-4614-5474-8]
18. Bedson J, Skrip LA, Pedi D, et al. A review and agenda for integrated disease models including social and behavioural factors. Nat Hum Behav. Jul 2021;5(7):834-846. [doi: 10.1038/s41562-021-01136-2] [Medline: 34183799]
19. Ryan M, Brindal E, Roberts M, Hickson RI. A behaviour and disease transmission model: incorporating the health belief model for human behaviour into a simple transmission model. J R Soc Interface. Jun 2024;21(215):20240038. [doi: 10.1098/rsif.2024.0038] [Medline: 38835247]
20. Ryan M, Brindal E, Hickson RI. Behaviour and infection feedback loops inform early-stage behaviour emergence and the efficacy of interventions. Math Med Life Sci. Dec 31, 2025;2(1):2452444. [doi: 10.1080/29937574.2025.2452444]
21. D'Agnese E, Melegaro A, Offeddu V, D'Onofrio A, Perra N, Bauch CT, et al. A systematic review of COVID-19 epidemic models with endogenous human behaviour. what's next? arXiv. Preprint posted online on Jun 9, 2026. [doi: 10.48550/arXiv.2606.12465]
22. Hamilton A, Haghpanah F, Tulchinsky A, et al. Incorporating endogenous human behavior in models of COVID-19 transmission: a systematic scoping review. Dialogues Health. Jun 2024;4:100179. [doi: 10.1016/j.dialog.2024.100179] [Medline: 38813579]
23. Funk S, Bansal S, Bauch CT, et al. Nine challenges in incorporating the dynamics of behaviour in infectious diseases models. Epidemics. Mar 2015;10:21-25. [doi: 10.1016/j.epidem.2014.09.005] [Medline: 25843377]
24. Perra N. Non-pharmaceutical interventions during the COVID-19 pandemic: a review. Phys Rep. May 23, 2021;913:1-52. [doi: 10.1016/j.physrep.2021.02.001] [Medline: 33612922]
25. De Gaetano A, Bajardi P, Gozzi N, Perra N, Perrotta D, Paolotti D. Behavioral changes associated with COVID-19 vaccination: cross-national online survey. J Med Internet Res. Oct 31, 2023;25:e47563. [doi: 10.2196/47563] [Medline: 37906219]
26. West R, Michie S, Rubin GJ, Amlôt R. Applying principles of behaviour change to reduce SARS-CoV-2 transmission. Nat Hum Behav. May 2020;4(5):451-459. [doi: 10.1038/s41562-020-0887-9] [Medline: 32377018]
27. Hill EM, Ryan M, Haw D, et al. Integrating human behaviour and epidemiological modelling: unlocking the remaining challenges. Math Med Life Sci. Dec 31, 2024;1(1):2429479. [doi: 10.1080/29937574.2024.2429479]
28. Michie S, van Stralen MM, West R. The behaviour change wheel: a new method for characterising and designing behaviour change interventions. Implement Sci. Apr 23, 2011;6(1):42. [doi: 10.1186/1748-5908-6-42] [Medline: 21513547]
29. Sheeran P, Webb TL. The intention–behavior gap. Soc Pers Psychol Compass. Sep 2016;10(9):503-518. [doi: 10.1111/spc3.12265]
30. Betsch C, Schmid P, Heinemeier D, Korn L, Holtmann C, Böhm R. Beyond confidence: development of a measure assessing the 5C psychological antecedents of vaccination. PLoS One. 2018;13(12):e0208601. [doi: 10.1371/journal.pone.0208601] [Medline: 30532274]
31. Graham J, Nosek BA, Haidt J, Iyer R, Koleva S, Ditto PH. Mapping the moral domain. J Pers Soc Psychol. Aug 2011;101(2):366-385. [doi: 10.1037/a0021847] [Medline: 21244182]
32. Davis R, Campbell R, Hildon Z, Hobbs L, Michie S. Theories of behaviour and behaviour change across the social and behavioural sciences: a scoping review. Health Psychol Rev. 2015;9(3):323-344. [doi: 10.1080/17437199.2014.941722] [Medline: 25104107]
33. Hagger MS, Cameron LD, Hamilton K, Hankonen N, Lintunen T. The Handbook of Behavior Change. 1st ed. Cambridge University Press; 2020. [doi: 10.1017/9781108677318]

34. Habersaat KB, Jackson C. Understanding vaccine acceptance and demand-and ways to increase them. Bundesgesundheitsblatt Gesundheitsforschung Gesundheitsschutz. Jan 2020;63(1):32-39. [doi: 10.1007/s00103-019-03063-0] [Medline: 31802154]
35. Michie S. Encouraging vaccine uptake: lessons from behavioural science. Nat Rev Immunol. Sep 2022;22(9):527-528. [doi: 10.1038/s41577-022-00769-2] [Medline: 35896830]
36. Vallis M, Bacon S, Corace K, et al. Ending the pandemic: how behavioural science can help optimize global COVID-19 vaccine uptake. Vaccines (Basel). Dec 22, 2021;10(1):7. [doi: 10.3390/vaccines10010007] [Medline: 35062668]
37. TIP: tailoring immunization programmes. World Health Organization. 2019. URL: https://www.who.int/europe/publications/i/item/9789289054492 [Accessed 2025-03-19]
38. Murphy K, Berk J, Muhwava-Mbabala L, et al. Using the COM-B model and behaviour change wheel to develop a theory and evidence-based intervention for women with gestational diabetes (IINDIAGO). BMC Public Health. May 15, 2023;23(1):894. [doi: 10.1186/s12889-023-15586-y] [Medline: 37189143]
39. World Health Organization. Pandemic Fatigue – Reinvigorating the Public to Prevent COVID-19. World Health Organization Regional Office for Europe; 2020. URL: https://iris.who.int/server/api/core/bitstreams/3ed4b3dc-e449-477e-8a0b-3c6fe2902c52/content [Accessed 2025-03-19]
40. Venkatesan S, Nguyen-Van-Tam JS, Siebers PO. A novel framework for evaluating the impact of individual decision-making on public health outcomes and its potential application to study antiviral treatment collection during an influenza pandemic. PLoS One. 2019;14(10):e0223946. [doi: 10.1371/journal.pone.0223946] [Medline: 31622404]
41. Betsch C, Bach Habersaat K, Deshevoi S, et al. Sample study protocol for adapting and translating the 5C scale to assess the psychological antecedents of vaccination. BMJ Open. Mar 10, 2020;10(3):e034869. [doi: 10.1136/bmjopen-2019-034869] [Medline: 32161160]
42. IMMUNE behavioural study. OSF Registries. URL: https://osf.io/mnb4k/overview [Accessed 2026-11-10]
43. Cint. URL: https://www.cint.com/ [Accessed 2026-10-22]
44. Database. Eurostat. 2021. URL: https://ec.europa.eu/eurostat/databrowser/explore/all/all_themes [Accessed 2025-04-07]
45. International standard classification of education (ISCED). Eurostat. 2026. URL: www.ec.europa.eu/eurostat/statistics-explained/index.php?title=International_Standard_Classification_of_Education_(ISCED) [Accessed 2026-10-22]
46. NUTS-nomenclature of territorial units for statistics. Eurostat. 2024. URL: https://ec.europa.eu/eurostat/web/nuts [Accessed 2025-03-24]
47. Cameron-Blake E, Tatlow H, Andretti B, et al. A panel dataset of COVID-19 vaccination policies in 185 countries. Nat Hum Behav. Aug 2023;7(8):1402-1413. [doi: 10.1038/s41562-023-01615-8] [Medline: 37414885]
48. Hoang T, Coletti P, Melegaro A, et al. A systematic review of social contact surveys to inform transmission models of close-contact infections. Epidemiology. Sep 2019;30(5):723-736. [doi: 10.1097/EDE.0000000000001047] [Medline: 31274572]
49. Mossong J, Hens N, Jit M, et al. Social contacts and mixing patterns relevant to the spread of infectious diseases. PLoS Med. Mar 25, 2008;5(3):e74. [doi: 10.1371/journal.pmed.0050074] [Medline: 18366252]
50. Eurostat. EU - Labour Force Survey Microdata 1983-2023. 2024. [doi: 10.2907/LFS1983-2023]
51. van Kleef E, Van Bortel W, Arsevska E, et al. Modelling practices, data provisioning, sharing and dissemination needs for pandemic decision-making: a European survey-based modellers' perspective, 2020 to 2022. Euro Surveill. Oct 2025;30(42):2500216. [doi: 10.2807/1560-7917.ES.2025.30.42.2500216] [Medline: 41133306]
52. Weston D, Ip A, Amlôt R. Examining the application of behaviour change theories in the context of infectious disease outbreaks and emergency response: a review of reviews. BMC Public Health. Oct 1, 2020;20(1):1483. [doi: 10.1186/s12889-020-09519-2] [Medline: 33004011]
53. Ajzen I. The theory of planned behavior. Organ Behav Hum Decis Process. Dec 1991;50(2):179-211. [doi: 10.1016/0749-5978(91)90020-T]
54. Fishbein M, Ajzen I. Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research. Addison-Wesley Publishing Company; 1975. ISBN: 0201020890
55. Rogers RW. A protection motivation theory of fear appeals and attitude change. J Psychol. Sep 1975;91(1):93-114. [doi: 10.1080/00223980.1975.9915803] [Medline: 28136248]
56. Sheeran P. Intention—behavior relations: a conceptual and empirical review. Eur Rev Soc Psychol. Jan 2002;12(1):1-36. [doi: 10.1080/14792772143000003]
57. Dhawan D, Kikut-Stein A, Pinnamaneni R, McCloud R, Viswanath K. Can we convince the unvaccinated to vaccinate: lessons from COVID-19 vaccination. BMC Public Health. May 7, 2025;25(1):1689. [doi: 10.1186/s12889-025-22911-0] [Medline: 40336037]

58. Gori D, Capodici A, La Fauci G, et al. COVID-19 vaccine refusal and delay among adults in Italy: evidence from the OBVIOUS project, a national survey in Italy. Vaccines (Basel). Apr 13, 2023;11(4):839. [doi: 10.3390/vaccines11040839] [Medline: 37112751]
59. Latkin C, Dayton L, Yi G, Jaleel A, Nwosu C, Limaye R. COVID-19 vaccine delay: an examination of United States residents' intention to delay vaccine uptake. Hum Vaccin Immunother. Sep 2, 2021;17(9):2903-2913. [doi: 10.1080/21645515.2021.1917234] [Medline: 34014130]
60. Fukai T, Kawata K, Nakabayashi M. Updated beliefs and shaken confidence: evidence from vaccine hesitancy caused by experiencing "COVID arm". BMC Infect Dis. Sep 18, 2023;23(1):612. [doi: 10.1186/s12879-023-08558-5] [Medline: 37723413]
61. Fan X, Zhao Y, Zhang X, et al. Vaccination burnout impedes the compliance with multiple-dose administration of vaccines. Sci Rep. 2025;15(1):13269. [doi: 10.1038/s41598-025-97959-4]
62. Stamm TA, Partheymüller J, Mosor E, et al. Determinants of COVID-19 vaccine fatigue. Nat Med. May 2023;29(5):1164-1171. [doi: 10.1038/s41591-023-02282-y] [Medline: 36973410]
63. Betsch C, Eitze S, Korn L, Felgendreff L, Tänzer AS, Sprengholz P. Dataset of 69 German COVID-19 Snapshot Monitoring (COSMO) surveys on pandemic attitudes, feelings and behaviours. Sci Data. Jun 23, 2025;12(1):1066. [doi: 10.1038/s41597-025-05275-3] [Medline: 40550795]
64. Agosti F, Toffolutti V, Cavalli N, Nivakoski S, Mascherini M, Aassve A. Information and vaccine hesitancy: evidence from the early stage of the vaccine roll-out in 28 European countries. PLoS One. 2022;17(9):e0273555. [doi: 10.1371/journal.pone.0273555] [Medline: 36129897]
65. Sabat I, Neumann-Böhme S, Barros PP, et al. Vaccine hesitancy comes in waves: longitudinal evidence on willingness to vaccinate against COVID-19 from seven European countries. Vaccine. Aug 14, 2023;41(36):5304-5312. [doi: 10.1016/j.vaccine.2023.07.017] [Medline: 37460356]
66. González-Castro JL, Ubillos-Landa S, Puente-Martínez A, Gracia-Leiva M. Perceived vulnerability and severity predict adherence to COVID-19 protection measures: the mediating role of instrumental coping. Front Psychol. 2021;12:674032. [doi: 10.3389/fpsyg.2021.674032] [Medline: 34295285]
67. Rattay P, Michalski N, Domanska OM, et al. Differences in risk perception, knowledge and protective behaviour regarding COVID-19 by education level among women and men in Germany. Results from the COVID-19 Snapshot Monitoring (COSMO) study. PLoS One. 2021;16(5):e0251694. [doi: 10.1371/journal.pone.0251694] [Medline: 33979413]
68. Valckx S, Crèvecoeur J, Verelst F, et al. Individual factors influencing COVID-19 vaccine acceptance in between and during pandemic waves (July-December 2020). Vaccine. Jan 3, 2022;40(1):151-161. [doi: 10.1016/j.vaccine.2021.10.073] [Medline: 34863621]
69. Röpcke A, Brinkmann C, Neumann-Böhme S, et al. Understanding health risk perception: insights from an eight-country panel study during the COVID-19 pandemic. J Public Health (Berl). May 2026;34(5):1173-1185. [doi: 10.1007/s10389-024-02351-7]
70. Espinoza B, Swarup S, Barrett CL, Marathe M. Heterogeneous adaptive behavioral responses may increase epidemic burden. Sci Rep. Jul 4, 2022;12(1):11276. [doi: 10.1038/s41598-022-15444-8] [Medline: 35788663]
71. Nguyen MM, Freedman AS, Cheung MA, et al. The complex interplay between risk tolerance and the spread of infectious diseases. J R Soc Interface. Apr 2025;22(225):20240486. [doi: 10.1098/rsif.2024.0486] [Medline: 40262640]
72. Jung YJ, Gagneux-Brunon A, Bonneton M, et al. Factors associated with COVID-19 vaccine uptake among French population aged 65 years and older: results from a national online survey. BMC Geriatr. Aug 2, 2022;22(1):637. [doi: 10.1186/s12877-022-03338-3] [Medline: 35918635]
73. Whitaker M, Elliott J, Gerard-Ursin I, et al. Profiling vaccine attitudes and subsequent uptake in 1·1 million people in England: a nationwide cohort study. The Lancet. Jan 2026;407(10526):350-362. [doi: 10.1016/S0140-6736(25)01912-9] [Medline: 41167207]
74. Smith LE, Sim J, Cutts M, et al. Psychosocial factors affecting COVID-19 vaccine uptake in the UK: a prospective cohort study (CoVAccS - Wave 3). Vaccine X. Apr 2023;13:100276. [doi: 10.1016/j.jvacx.2023.100276] [Medline: 36819214]
75. Lun P, Ning K, Wang Y, et al. COVID-19 vaccination willingness and reasons for vaccine refusal. JAMA Netw Open. Oct 2, 2023;6(10):e2337909. [doi: 10.1001/jamanetworkopen.2023.37909] [Medline: 37856125]
76. Antonopoulou V, Ong M, Meyer C. Adherence to mask wearing and social distancing following vaccination and use of lateral flow testing during the COVID-19 pandemic in England and Wales: results from a cross-sectional study nested within the prospective virus watch household community cohort study. Discov Public Health. 2026;23(1):47. [doi: 10.1186/s12982-026-01375-6] [Medline: 41556063]

77. Chen J, Espinoza B, Chou J, Gumel AB, Levin SA, Marathe M. A simple model of coupled individual behavior and its impact on epidemic dynamics. Math Biosci. Feb 2025;380:109345. [doi: 10.1016/j.mbs.2024.109345] [Medline: 39694323]
78. Teslya A, Rozhnova G, Pham TM, et al. The importance of sustained compliance with physical distancing during COVID-19 vaccination rollout. Commun Med (Lond). Nov 19, 2022;2(1):146. [doi: 10.1038/s43856-022-00207-3] [Medline: 36402924]
79. Bauch CT, Galvani AP. Social factors in epidemiology. Science. Oct 4, 2013;342(6154):47-49. [doi: 10.1126/science.1244492] [Medline: 24092718]
80. Buonomo B, Della Marca R, d'Onofrio A, Groppi M. A behavioural modelling approach to assess the impact of COVID-19 vaccine hesitancy. J Theor Biol. Feb 7, 2022;534:110973. [doi: 10.1016/j.jtbi.2021.110973] [Medline: 34896166]
81. LeJeune L, Ghaffarzadegan N, Childs LM, Saucedo O. Formulating human risk response in epidemic models: exogenous vs endogenous approaches. Eur J Oper Res. Jul 2025;324(1):246-258. [doi: 10.1016/j.ejor.2025.01.004]
82. Sonubi B. Recall bias. Catalog of Bias. URL: https://catalogofbias.org/biases/recall-bias [Accessed 2026-08-18]
83. Roese NJ, Vohs KD. Hindsight bias. Perspect Psychol Sci. Sep 2012;7(5):411-426. [doi: 10.1177/1745691612454303] [Medline: 26168501]
84. Bethlehem J. Selection bias in web surveys. Int Statistical Rev. Aug 2010;78(2):161-188. [doi: 10.1111/j.1751-5823.2010.00112.x]
85. Rodríguez-Blázquez C, Romay-Barja M, Falcón M, Ayala A, Forjaz MJ. The COSMO-Spain survey: three first rounds of the WHO behavioral insights tool. Front Public Health. 2021;9:678926. [doi: 10.3389/fpubh.2021.678926] [Medline: 34136459]
86. Lepola P, Kindred M, Giannuzzi V, et al. Informed consent and assent guide for paediatric clinical trials in Europe. Arch Dis Child. Jun 2022;107(6):582-590. [doi: 10.1136/archdischild-2021-322798] [Medline: 34853000]
87. Lepola P, Needham A, Mendum J, Sallabank P, Neubauer D, de Wildt S. Informed consent for paediatric clinical trials in Europe. Arch Dis Child. Nov 2016;101(11):1017-1025. [doi: 10.1136/archdischild-2015-310001] [Medline: 27226526]
88. de Winter JP, Toelen J, Milani GP, Hadjipanayis A, EAP Collaborators. A survey of the legal frameworks on medical decision-making in minors in European countries. Eur J Pediatr. Nov 25, 2024;184(1):43. [doi: 10.1007/s00431-024-05836-5] [Medline: 39586871]
89. Delgado JR, Szilagyi PG, Peralta JB, et al. Influence of Perceived Adolescent Vaccination Desire on Parent Decision for Adolescent COVID-19 Vaccination. J Adolesc Health. Apr 2022;70(4):567-570. [doi: 10.1016/j.jadohealth.2022.01.121] [Medline: 35305793]
90. Harris MJ, Sinclair AH, Pullano G, et al. Emerging frontiers in infectious disease modelling: reassessing the data-driven feedback loop between human behaviour and disease dynamics. R Soc Open Sci. Jun 3, 2026;13(6):260369. [doi: 10.1098/rsos.260369]
91. Funk S, Salathé M, Jansen VAA. Modelling the influence of human behaviour on the spread of infectious diseases: a review. J R Soc Interface. Sep 6, 2010;7(50):1247-1256. [doi: 10.1098/rsif.2010.0142] [Medline: 20504800]
92. Karsai M, Koltai J, Vásárhelyi O, Röst G. Hungary in Mask/MASZK in Hungary. Corvinus J Sociol Soc Policy. Nov 2020:139-146. [doi: 10.14267/CJSSP.2020.2.9]
93. Salomon JA, Reinhart A, Bilinski A, et al. The US COVID-19 trends and impact survey: continuous real-time measurement of COVID-19 symptoms, risks, protective behaviors, testing, and vaccination. Proc Natl Acad Sci U S A. Dec 21, 2021;118(51):e2111454118. [doi: 10.1073/pnas.2111454118] [Medline: 34903656]
94. Johns Hopkins Center for Communication Programs. COVID Behaviors Dashboard; 2026. URL: https://ccp.jhu.edu/kap-covid/ [Accessed 2026-11-03]
95. Bokányi E, Vizi Z, Koltai J, Röst G, Karsai M. Real-time estimation of the effective reproduction number of COVID-19 from behavioral data. Sci Rep. Dec 5, 2023;13(1):21452. [doi: 10.1038/s41598-023-46418-z] [Medline: 38052841]
96. Kretzschmar ME, Ashby B, Fearon E, et al. Challenges for modelling interventions for future pandemics. Epidemics. Mar 2022;38:100546. [doi: 10.1016/j.epidem.2022.100546] [Medline: 35183834]
97. Jit M, Ainslie K, Althaus C, et al. Reflections on epidemiological modeling to inform policy during the COVID-19 pandemic in Western Europe, 2020–23. Health Aff. Dec 1, 2023;42(12):1630-1636. [doi: 10.1377/hlthaff.2023.00688]
98. INF-ACT Foundation. BEHAVE-MOD Monitoraggio e Modellizzazione del Comportamento e del Sentimento per il Controllo degli Epidemie. 2026. URL: https://www.inf-act.it/progetti/inf-act/bando-a-cascata-rn4-behave-mod/ [Accessed 2026-10-23]
99. About influweb. Influweb. URL: https://influweb.org/about [Accessed 2025-06-13]
100. Influenzanet homepage. Influenzanet. 2026. URL: https://influenzanet.info/home [Accessed 2026-10-23]

101. Koltai J, Vásárhelyi O, Röst G, Karsai M. Reconstructing social mixing patterns via weighted contact matrices from online and representative surveys. Sci Rep. Mar 18, 2022;12(1):4690. [doi: 10.1038/s41598-022-07488-7] [Medline: 35304478]
102. Koher A, Jørgensen F, Petersen MB, Lehmann S. Epidemic modelling of monitoring public behavior using surveys during pandemic-induced lockdowns. Commun Med (Lond). Jun 8, 2023;3(1):80. [doi: 10.1038/s43856-023-00310-z] [Medline: 37291090]
103. Lyu H, Imtiaz A, Zhao Y, Luo J. Human behavior in the time of COVID-19: learning from big data. Front Big Data. 2023;6:1099182. [doi: 10.3389/fdata.2023.1099182] [Medline: 37091459]
104. Lu Y, Aleta A, Du C, Shi L, Moreno Y. LLMs and generative agent-based models for complex systems research. Phys Life Rev. Dec 2024;51:283-293. [doi: 10.1016/j.plrev.2024.10.013]
105. Kraemer MUG, Tsui JLH, Chang SY, et al. Artificial intelligence for modelling infectious disease epidemics. Nature. Feb 2025;638(8051):623-635. [doi: 10.1038/s41586-024-08564-w] [Medline: 39972226]
106. Delfraissy JF, Yazdanpanah Y, Levy Y. REACTing: the French response to infectious disease crises. The Lancet. May 2016;387(10034):2183-2185. [doi: 10.1016/S0140-6736(16)30059-9]
107. Wijermans N, Schill C, Lindahl T, Schlüter M. Combining approaches: looking behind the scenes of integrating multiple types of evidence from controlled behavioural experiments through agent-based modelling. Int J Soc Res Methodol. Jul 4, 2022;25(4):569-581. [doi: 10.1080/13645579.2022.2050120]
108. Lighthouse: a community of practice by ECDC. European Centre for Disease Prevention and Control. 2025. URL: https://prevention.ecdc.europa.eu/public-home [Accessed 2025-05-23]
109. One health initiative. World Health Organization. 2025. URL: https://www.who.int/teams/one-health-initiative [Accessed 2025-05-24]

Abbreviations

COM-B: capability, opportunity, and motivation-behavior
GDPR: General Data Protection Regulation
NUTS: Nomenclature of Territorial Units for Statistics
OSF: Open Science Framework

Edited by Stefano Brini; peer-reviewed by Huseyin Atakan Varol, Matt Ryan, Zeyao Zhao; submitted 28.May.2026; final revised version received 21.Aug.2026; accepted 26.Aug.2026; published 26.Nov.2026

Please cite as:
Offeddu V, Colosi E, Lucchini L, Leone LP, Chiavenna C, Balsamo D, D'Agnese E, Bonacina F, Cucciniello M, Trentini F, Aleta A, Manfredi P, Moreno Y, Karsai M, Colizza V, Koltai J, Melegaro A
Developing an Interdisciplinary Framework for Behavioral Data Collection to Advance Coupled Behavioral-Epidemic Models: Cross-Sectional Study in 6 European Countries
J Med Internet Res 2026;28:e102346
URL: https://www.jmir.org/2026/1/e102346
doi: 10.2196/102346

© Vittoria Offeddu, Elisabetta Colosi, Lorenzo Lucchini, Laura P Leone, Chiara Chiavenna, Duilio Balsamo, Elena D'Agnese, Francesco Bonacina, Maria Cucciniello, Filippo Trentini, Alberto Aleta, Piero Manfredi, Yamir Moreno, Márton Karsai, Vittoria Colizza, Júlia Koltai, Alessia Melegaro. Originally published in the Journal of Medical Internet Research (https://www.jmir.org), 26.Nov.2026. This is an open-access article distributed under the terms of the Creative Commons Attribution License (https://creativecommons.org/licenses/by/4.0/), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work, first published in the Journal of Medical Internet Research (ISSN 1438-8871), is properly cited. The complete bibliographic information, a link to the original publication on https://www.jmir.org/, as well as this copyright and license information must be included.