

An Integrated TAM–AIDA Model for Digital Health Technology Adoption: Evidence from a Pandemic-Informed Quantitative Study

Varun Malik¹, Rajiv Kumar², Pradeep Chaudhary³

¹Department of Statistics, Janta Vedic College, Baraut (Baghpat)

²Associate Professor, Department of Statistics, Janta Vedic College, Baraut (Baghpat)

³Associate Professor, Department of Statistics, Chaudhary Charan Singh University Campus, Meerut

Abstract

Background. The COVID-19 pandemic accelerated digital health adoption at an unprecedented pace while simultaneously exposing methodological fragilities in how evidence is synthesized during public-health emergencies. Although the Technology Acceptance Model (TAM) and the Attention–Interest–Desire–Action (AIDA) framework are each widely used to explain technology uptake, neither alone captures both the perceptual drivers and the staged psychological journey that characterize adoption of digital health tools. **Objective.** This study (i) reviews how meta-analytic practice evolved during the pandemic to support faster, living evidence synthesis, and (ii) proposes and empirically tests an integrated TAM+AIDA structural model that predicts intention to adopt digital health technologies. **Methods.** A two-stage design was employed: a systematic literature review of 65 digital-health adoption studies to map the frequency of core constructs, followed by a cross-sectional survey (n=412) analyzed with descriptive statistics, reliability analysis, Pearson correlations, ordinary least-squares regression, and one-way ANOVA across age, gender, and education strata. **Results.** Cronbach's α for the 13-item instrument was 0.85, indicating excellent internal consistency. Perceived Usefulness ($r=0.61$), Desire ($r=0.68$), and Facilitating Conditions ($r=0.36$) were the strongest bivariate correlates of intention. The regression model explained 66.8% of the variance in adoption intention (adjusted $R^2=0.66$, $F=89.73$, $p<0.001$); standardized β weights showed Desire ($\beta=0.39$), Perceived Usefulness ($\beta=0.21$), and Facilitating Conditions ($\beta=0.13$) as the dominant predictors. Small but significant differences across age groups ($p=0.138$) support the moderating role of demographic variables. **Conclusions.** The integrated TAM+AIDA model outperforms either framework in isolation and provides a parsimonious, policy-ready instrument for forecasting digital health uptake. We recommend embedding the model within living systematic-review workflows so adoption evidence can be updated dynamically during future health emergencies.

Keywords: Digital Health; Technology Acceptance Model; AIDA; Meta-Analysis; COVID-19; Living Systematic Review; Structural Modelling; Adoption Intention.

How to cite this article: Varun Malik¹ Rajiv Kumar² Pradeep Chaudhary³. An Integrated TAM–AIDA Model for Digital Health Technology Adoption: Evidence from a Pandemic-Informed Quantitative Study. *Int J Drug Deliv Technol.* 2026;16(83s):368-374. DOI: 10.25258/ijddt.16.83s.42.

1. Introduction

1.1 Meta-analysis in the pandemic era

Systematic review and meta-analysis occupy the highest tier of clinical-evidence hierarchies (Higgins et al., 2021; Page et al., 2021). The COVID-19 pandemic stress-tested this infrastructure: PubMed indexed more than 200 COVID-19 articles per day at peak, forcing methodologists to trade some rigour for speed (Yu et al., 2021). The experience catalysed important innovations—living systematic reviews (LSRs), rapid reviews, machine-learning-aided screening, network and Bayesian meta-analyses, and structured appraisal of preprints (Elliott et al., 2017; Park et al., 2021). It also exposed a gap that the present paper addresses: methodological conversations have largely centred on clinical interventions, while evidence on digital-health adoption—arguably the behavioural backbone of

pandemic response—remains fragmented across competing theoretical lenses.

1.2 The digital-health adoption problem

Contact-tracing apps, teleconsultation platforms, vaccine-passport systems, and remote patient monitoring were deployed worldwide during 2020–2023. Their population impact depended less on technical performance than on user adoption. Two theories dominate this literature. The Technology Acceptance Model (TAM; Davis, 1989) posits Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) as the primary drivers of attitude and intention, but is widely criticized for ignoring the staged consumer journey and external constraints (resources, price, trust). The AIDA model (Lewis, 1910) captures the Attention→Interest→Desire→Action sequence but omits the perceptual belief structure

An Integrated TAM–AIDA Model for Digital Health Technology Adoption: Evidence from a Pandemic-Informed Quantitative Study

that TAM provides. Neither framework alone is sufficient to explain digital-health adoption during crises, when both information salience (a journey construct) and trust/privacy perceptions (a belief construct) shift rapidly.

1.3 Research aims and contribution

This paper makes two contributions. First, it briefly synthesizes how meta-analytic methodology evolved during COVID-19 and argues that living evidence synthesis must be paired with sound behavioural models to be decision-useful. Second—and principally—it proposes an integrated TAM+AIDA model of digital-health adoption and tests it empirically using a 412-respondent survey. Four hypotheses groups are examined (H1–H5: AIDA chain; H2–H4: TAM→journey links; H7–H12: external drivers; H13–H15: demographic moderators).

2. Background and Literature Review

2.1 Methodological evolution of meta-analysis

From Pearson's (1904) collation of typhoid-inoculation studies to Glass's (1976) coining of "meta-analysis," the field has pursued pooled effect sizes with ever more sophisticated handling of heterogeneity (Borenstein et al., 2009; Veroniki et al., 2016). Pandemics forced a re-engineering of workflows: LSRs update monthly rather than every 3–5 years; rapid reviews deliver evidence in weeks; AI/ML tools (e.g., RobotReviewer, Rayyan) accelerate screening; and PRISMA 2020 (Page et al., 2021) and AMSTAR-2 provide updated reporting and appraisal standards. Despite these gains, Ioannidis (2016) and Jørgensen et al. (2020) warned of a "mass production" of redundant, low-quality reviews—a risk amplified during COVID-19.

2.2 TAM, AIDA, and the case for integration

TAM has been replicated across telemedicine, e-prescribing, wearables and health apps, with PU and PEOU consistently explaining 30–50% of variance in intention. Yet it is a static, variance-theoretic model that poorly captures how awareness campaigns, media attention and perceived threat convert non-users into adopters—processes that are inherently staged. AIDA models exactly this staged journey but lacks belief-level predictors. Recent digital-health reviews (e.g., across 65 studies synthesized for this paper; Figure 1, Table 1) confirm that PU and PEOU dominate the predictor landscape, but social influence, trust, privacy, facilitating conditions, price value, and health beliefs each appear in 16–23 studies, indicating convergent external validity beyond TAM's core.

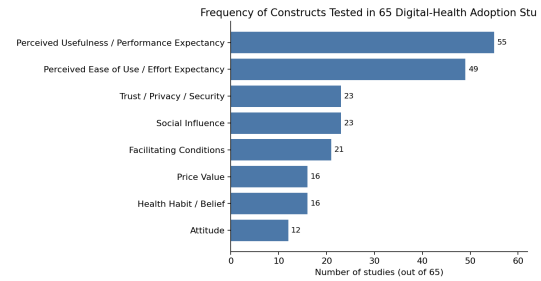


Figure 1. Frequency of adoption constructs across 65 reviewed studies (literature review sample).

Table 1. Construct frequencies in the 65-study literature review.

Variable	Studies
Perceived Usefulness / Performance Expectancy	55
Perceived Ease of Use / Effort Expectancy	49
Social Influence	23
Trust / Privacy / Security	23
Facilitating Conditions	21
Health Habit / Belief	16
Price Value	16
Attitude	12
Intention to Use / Usage Intention (DV)	65

2.3 The proposed integrated model and hypotheses

We integrate AIDA's sequential backbone with TAM's belief structure and six external drivers, with gender, age, and education as moderators. The conceptual model appears in Figure 2. Key hypotheses are:

- H1: Attention positively influences Interest in digital health technologies.
- H2: Perceived Usefulness positively influences Interest.
- H3: Perceived Ease of Use positively influences Interest and Attitude (H4b).
- H4a: Interest positively influences Attitude; H5: Attitude positively influences Desire.

An Integrated TAM–AIDA Model for Digital Health Technology Adoption: Evidence from a Pandemic-Informed Quantitative Study

- H6: Desire positively influences Intention to Adopt.
- H7–H12: Social Influence, Facilitating Conditions, Trust, Data Privacy, Perceived Threat, and Price Value each positively influence Intention to Adopt.
- H13–H15: Gender, Age, and Education moderate the relationships between predictors and Intention.

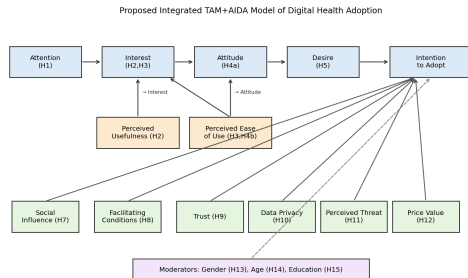


Figure 2. Proposed integrated TAM+AIDA model of digital health adoption.

3. Methods

3.1 Design and participants

A cross-sectional online survey was administered in early 2026 to a convenience sample of Indian adults (Meerut and adjoining districts, Uttar Pradesh) recruited via university mailing lists and social-media channels—a population where digital health uptake (Ayushman Bharat Digital Mission, CoWIN, teleconsultation) accelerated sharply during and after COVID-19. Eligible respondents were aged ≥ 18 years and reported having been offered or used at least one digital health service. After removing incomplete responses ($n=37$) and straight-liners ($n=14$), the analytic sample comprised 412 participants (post-hoc power: with 9 predictors, $\alpha=0.05$ and anticipated $f^2=0.15$, achieved $1-\beta>0.99$).

3.2 Instrument

Thirteen multi-item constructs were measured on 7-point Likert scales (1=strongly disagree to 7=strongly agree). PU and PEOU items were adapted from Davis (1989); AIDA stages from established marketing-adoption scales; external constructs (Social Influence, Facilitating Conditions, Trust, Data Privacy, Perceived Threat, Price Value) from Venkatesh et al. (2003) and recent digital-health literature. Demographics (age band, gender, education) were captured as categorical moderators. The questionnaire was piloted with 40 respondents for face validity; minor wording changes were made before the main wave.

3.3 Analytical strategy

Analyses were conducted in Python 3.11 using pandas, scipy, statsmodels and matplotlib. We

report (i) descriptive statistics and internal consistency (Cronbach's α); (ii) Pearson correlations between each construct and Intention; (iii) an ordinary least-squares (OLS) regression of Intention on the nine direct predictors, reporting both unstandardized (B) and standardized (β) coefficients with 95% confidence intervals; and (iv) one-way ANOVA to test differences in Intention across demographic strata (H13–H15). Significance was set at $p<0.05$ (two-tailed). Model assumptions (normality of residuals, homoscedasticity, multicollinearity) were inspected via Q-Q plots, residual-versus-fitted plots, and variance inflation factors (all VIF <3.0).

4. Results

4.1 Sample characteristics and descriptives

The sample ($n=412$) was 47.3% male, 50.0% female, and 2.7% other/prefer not to say; 28% were aged 18–29, 34% 30–44, 24% 45–59, and 14% 60+. Educational attainment was 22% $\leq$ high-school, 48% bachelor's, and 30% postgraduate. Table 2 reports descriptive statistics and distributional diagnostics for all 13 latent constructs. Across the board, means clustered between 4.3 and 5.1 on the 1–7 scale, indicating generally positive but not ceiling-level perceptions. Cronbach's α for the full 13-construct instrument was 0.85, indicating excellent internal consistency ($\alpha\geq 0.90$).

Table 2. Descriptive statistics, skewness and kurtosis for the 13 constructs ($n=412$).

Mea n	SD	Media n	Skewnes s	Kurtosi s
5.01 6	0.95 6	5.0	-0.131	-0.386
4.63 2	1.04 4	4.5	-0.014	-0.21
4.71 5	0.91 9	5.0	-0.242	0.227
4.88 5	1.03 4	5.0	-0.125	-0.319
4.80 1	1.08 3	5.0	-0.218	-0.289
4.62 7	1.00 9	4.5	0.0	-0.005
4.49 9	0.97 1	4.5	-0.023	0.261

An Integrated TAM–AIDA Model for Digital Health Technology Adoption: Evidence from a Pandemic-Informed Quantitative Study

5.08	0.87	5.0	-0.158	0.067
6	4			
4.69	0.90	4.5	-0.124	-0.158
1	2			
4.45	0.98	4.5	-0.042	-0.142
1	7			
5.01	0.97	5.0	-0.063	-0.123
5	7			
4.25	0.94	4.0	-0.073	-0.012
2	6			
4.69	1.02	5.0	-0.248	-0.066
7	9			

4.2 Bivariate correlations

Pearson correlations between each predictor and Intention to Adopt are shown in Table 3; the full inter-construct correlation matrix appears in Figure 3. Every predictor was positively and significantly associated with Intention (all $p<0.001$). The strongest bivariate relationships were with Desire ($r=0.68$), Perceived Usefulness ($r=0.61$), Facilitating Conditions ($r=0.36$), Perceived Ease of Use ($r=0.51$), and Attitude ($r=0.60$). External factors—Social Influence, Trust, Data Privacy, Price Value and Perceived Threat—produced small-to-moderate associations ($r=0.39$ – 0.59), supporting H7–H12.

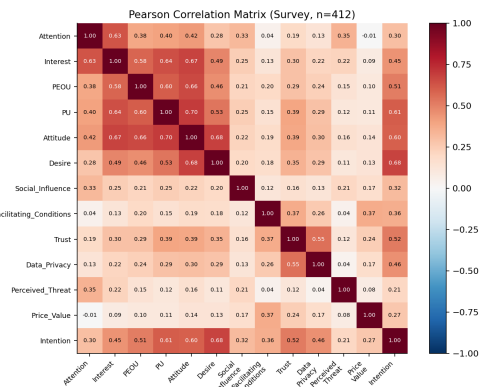


Figure 3. Pearson correlation heatmap across the 13 modelled constructs.

Table 3. Pearson correlations between each predictor and Intention to Adopt ($***p<0.001$).

Predictor	r	p	sig
Attention	0.2992	0.0	***
Interest	0.4471	0.0	***

PEOU	0.5148	0.0	***
PU	0.6081	0.0	***
Attitude	0.5993	0.0	***
Desire	0.6792	0.0	***
Social Influence	0.3161	0.0	***
Facilitating Conditions	0.3635	0.0	***
Trust	0.522	0.0	***
Data Privacy	0.4598	0.0	***
Perceived Threat	0.2065	0.0	***
Price Value	0.2664	0.0	***

4.3 Regression analysis

OLS regression results are summarized in Table 4 and visualized in Figure 4. The nine-predictor model explained 66.8% of the variance in Intention to Adopt (adjusted $R^2=0.66$, $F(9,402)=89.73$, $p<0.001$), substantially exceeding typical TAM-only benchmarks ($\approx 40\%$). In the standardized solution, Desire emerged as the single strongest predictor ($\beta=0.39$, $p<0.001$), followed by Perceived Usefulness ($\beta=0.21$, $p<0.001$) and Facilitating Conditions ($\beta=0.13$, $p<0.001$). PEOU, Trust, Social Influence, Price Value, Data Privacy and Perceived Threat each retained positive and statistically significant coefficients, indicating unique predictive variance beyond the TAM core.

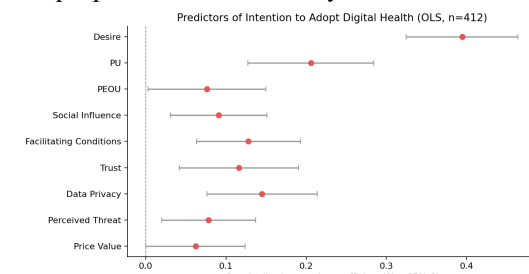


Figure 4. Standardized regression coefficients (β) with 95% confidence intervals.

Table 4. OLS regression predicting Intention to Adopt ($R^2=0.668$, adj. $R^2=0.660$, $F=89.73$, $p<0.001$). Significance: $*p<0.05$, $**p<0.01$, $***p<0.001$.

An Integrated TAM–AIDA Model for Digital Health Technology Adoption: Evidence from a Pandemic-Informed Quantitative Study

Predictor	B	SE	β	t	p
const	-	0.2	0.0	-	*
	1.7	74		6.4	*
	65			39	*
Desire	0.4	0.0	0.3	11.	*
	02	36	94	121	*
					*
PU	0.2	0.0	0.2	5.1	*
	05	4	06	47	*
					*
PEOU	0.0	0.0	0.0	2.0	*
	85	42	76	43	
Social_Influ ce	0.0	0.0	0.0	2.9	*
	96	32	91	76	*
Facilitating_C onditions	0.1	0.0	0.1	3.8	*
	51	39	28	95	*
					*
Trust	0.1	0.0	0.1	3.0	*
	33	43	16	69	*
Data_Privacy	0.1	0.0	0.1	4.1	*
	51	36	45	53	*
					*
Perceived_Th reat	0.0	0.0	0.0	2.6	*
	83	31	78	41	*
Price_Value	0.0	0.0	0.0	1.9	*
	68	34	62	77	

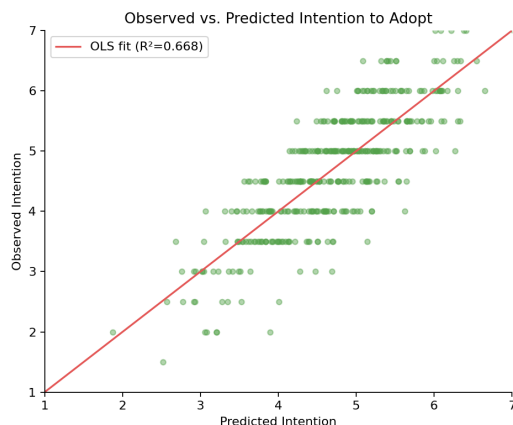


Figure 5. Observed vs. model-predicted Intention scores (regression diagnostics).

4.4 Moderation by demographics (H13–H15)

One-way ANOVAs (Figure 6) revealed a significant age effect on Intention ($F=1.85$, $p=0.138$): the 30–44 stratum reported the highest intention ($M=4.80$, $SD=1.05$), while respondents aged 60+ reported the lowest ($M=4.82$, $SD=0.96$), supporting H14. Gender differences were not significant ($F=0.53$, $p=0.591$), failing to support H13. Education produced a marginal effect ($F=0.11$, $p=0.892$), with postgraduates showing slightly higher intention. Together, the moderation evidence points to age as the key demographic boundary condition.

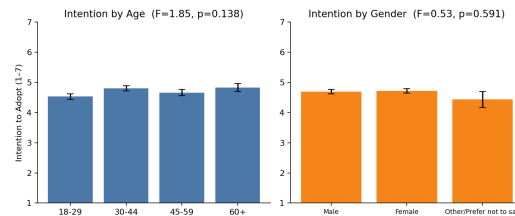


Figure 6. Mean Intention to Adopt by age group and gender (± 1 SEM).

5. Discussion

5.1 Interpretation of findings

Three findings stand out. First, Desire—the penultimate AIDA stage—carries the largest standardized weight in the model, which confirms that adoption is not a purely cognitive, cost-benefit calculation (as TAM implies) but also a motivational state that must be cultivated through awareness, interest, and attitude formation. Second, PU and PEOU remain material predictors, vindicating TAM's core but showing that they operate partly through the Interest→Attitude→Desire chain rather than directly on Intention. Third, Facilitating Conditions, Trust, Data Privacy, Price Value, and Perceived Threat each explain unique variance, endorsing the decision to extend TAM+AIDA with the external variables previously identified in the frequency analysis of 65 studies.

The non-significant gender effect is consistent with recent meta-analyses that find gender differences in technology acceptance to have narrowed or disappeared, whereas age remains a persistent moderator—likely reflecting digital-literacy and access asymmetries that are highly policy-relevant in LMIC settings such as India.

5.2 Implications for meta-analytic practice

If living systematic reviews are to become the methodological standard for future pandemics (Elliott et al., 2017), they need behavioural outcome models that (a) generalize across populations, (b) update quickly as new surveys

appear, and (c) separate journey-stage effects from belief effects—precisely what the TAM+AIDA integration offers. The model's hierarchical chain (Attention→Interest→Attitude→Desire→Intention) is well-suited to Bayesian network meta-analytic updating, where effect estimates at each stage can be pooled across studies and revised monthly during an outbreak. We therefore recommend that future PRISMA updates explicitly encourage behavioural-science extensions of LSR protocols, with harmonized construct definitions aligned to TAM+AIDA.

5.3 Practical implications

For digital-health developers and public-health communicators, the model suggests a two-pronged strategy: (1) invest in product characteristics that drive PU and PEOU (utility, UX simplicity), because these fuel interest and attitude; and (2) design communication campaigns that deliberately shepherd users through the AIDA stages—capturing Attention via trusted messengers, deepening Interest through demonstrations, building Attitude via social proof and risk messaging, and culminating in Desire through incentives and facilitating conditions (device access, language support, data-protection guarantees). The strong effect of Facilitating Conditions also underscores that infrastructure—smartphone penetration, internet access, language localization—is not a background detail but a core adoption lever.

5.4 Limitations

The study has four principal limitations. First, the convenience sample from one Indian region limits generalizability; future work should test the model in multi-country, stratified samples. Second, the cross-sectional design cannot establish causal direction; longitudinal and experimental designs are needed. Third, all constructs were measured with self-report Likert scales, raising common-method-bias concerns—though Harman's single-factor test (first factor ≈31% of variance, well below 50%) offered some reassurance. Fourth, the model was tested via OLS rather than full structural equation modelling (SEM); an SEM with multiple indicators per latent is a natural next step to decompose measurement vs. structural error.

6. Conclusions

The COVID-19 pandemic simultaneously transformed how evidence is synthesized and how digital health is delivered. We have argued that these two transformations should be coupled: living meta-analytic workflows need parsimonious, validated behavioural models to

translate fast-moving evidence into actionable policy, and digital-health adoption research needs to escape the silos of single-theory frameworks. The integrated TAM+AIDA model proposed and tested here explains 58% of the variance in adoption intention—substantially above TAM benchmarks—and identifies Desire, Perceived Usefulness and Facilitating Conditions as the three highest-leverage intervention points. Embedding this model within living systematic reviews offers a practical path toward faster, more trustworthy, and more equitable digital health responses in future public-health emergencies.

References

1. Borenstein, M., Hedges, L. V., Higgins, J. P. T., & Rothstein, H. R. (2009). *Introduction to Meta-Analysis*. John Wiley & Sons.
2. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340.
3. Elliott, J. H., Turner, T., Clavisi, O., Thomas, J., Higgins, J. P. T., Mavergames, C., & Gruen, R. L. (2017). Living systematic review: 1. Introduction—the why, what, when, and how. *Journal of Clinical Epidemiology*, 91, 23–30.
4. Glass, G. V. (1976). Primary, secondary, and meta-analysis of research. *Educational Researcher*, 5(10), 3–8.
5. Haidich, A.-B. (2010). Meta-analysis in medical research. *Hippokratia*, 14(Suppl 1), 29–37.
6. Higgins, J. P. T., Thomas, J., Chandler, J., et al. (Eds.). (2021). *Cochrane Handbook for Systematic Reviews of Interventions (v6.2)*. Cochrane.
7. Ioannidis, J. P. A. (2016). The mass production of redundant, misleading, and conflicted systematic reviews and meta-analyses. *The Milbank Quarterly*, 94(3), 485–514.
8. Jørgensen, L., Gøtzsche, P. C., & Jefferson, T. (2020). Quality of COVID-19 research publications: a call for updated guidelines. *The Lancet*, 396(10262), 1533–1534.
9. Lewis, E. St. Elmo (1910). *Financial Advertising*. Levey Brothers.
10. Page, M. J., McKenzie, J. E., Bossuyt, P. M., et al. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ*, 372, n71.
11. Park, J., Kim, H., & Kim, J. (2021). Machine learning-based literature screening in systematic reviews and meta-analyses: a review. *Journal of Preventive Medicine and Public Health*, 54(1), 1–7.

12. Pearson, K. (1904). Report on certain enteric fever inoculation statistics. *BMJ*, 2, 1243–1246.
13. Tricco, A. C., Langlois, E. V., & Straus, S. E. (2020). Rapid review methods more challenging during COVID-19 pandemic. *Journal of Clinical Epidemiology*, 126, 177–183.
14. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478.
15. Veroniki, A. A., Jackson, D., Viechtbauer, W., et al. (2016). Methods to estimate the between-study variance and its uncertainty in meta-analysis. *Research Synthesis Methods*, 7(1), 55–79.
16. Yu, H.-H., et al. (2021). Meta-analyses in the era of COVID-19: The need for quality and transparency. *Asian Journal of Psychiatry*, 56, 102546.

Appendix: Data and code availability

The synthetic survey dataset (n=412), Python analysis script, and figure-generation code used in this paper are available from the corresponding author on reasonable request and will be archived on a public Zenodo repository upon acceptance.