International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(17s) 2026 pp. 697-705
https://doi.org/10.70917/ijcisim-2026-4793
Article

Does AI Build Financial Confidence? A Structural Equation Model of AI Usage, Financial Self-Efficacy, and Financial Behaviour among Generation Z

A. Saravanan[1], G. John[2]

[1]Department of Commerce, St. Joseph's College (Autonomous), affiliated to Bharathidasan University, Tiruchirappalli, Tamil Nadu, India.
Email: saravanan_phdco@mail.sjctni.edu
[2]Department of Commerce, St. Joseph's College (Autonomous), affiliated to Bharathidasan University, Tiruchirappalli, Tamil Nadu, India.

Abstract: Generation Z has come of age alongside a rapid expansion of artificial-intelligence (AI)-enabled financial technologies, including robo-advisors, chatbot-based budgeting assistants, and algorithmic investment platforms. While digital financial literacy and social-media exposure are established predictors of young adults' financial self-efficacy and saving behaviour, the specific contribution of AI-tool usage remains comparatively under-examined. This study proposes and tests a structural model in which AI usage/reliance (AIU) predicts financial behaviour (FB) both directly and indirectly through financial self-efficacy (FSE), controlling for financial literacy (FL). Data are collected from a stratified random sample of 350+ Gen Z respondents (ages 18–27), stratified by gender, region, and income band. Measurement and structural parameters are estimated via structural equation modelling (SEM; WLSMV estimator for ordinal indicators), following confirmatory factor analysis of four latent constructs. This manuscript presents the full analytical framework variable definitions, sampling design, descriptive and inferential statistics, SEM specification, model-fit criteria, and visualization plan together with a reproducible R/Python pipeline.
Keywords: Artificial Intelligence; Financial Self-Efficacy; Financial Behaviour; Generation Z; Structural Equation Modelling; Fintech; Financial Literacy

1. Introduction

Generation Z commonly defined as those born between the mid-1990s and early 2010s is the first cohort to have reached financial independence inside an ecosystem of AI-mediated financial tools: robo-advisors, algorithmic budgeting apps, and conversational finance assistants embedded in mainstream banking apps. Industry survey data indicate that a substantial majority of Gen Z consumers already use, or intend to use, generative AI for everyday money tasks such as budgeting, saving, and investment planning, with many reporting a level of trust in AI-generated financial guidance comparable to that placed in human advisors (Experian, 2024, as cited in ScienceDirect, 2026).

At the same time, large-scale literacy assessments continue to find that Gen Z scores the lowest of any adult cohort on standardized financial-knowledge tests, despite being highly active on digital financial platforms (TIAA Institute–GFLEC, 2025). This apparent paradox high technology engagement alongside persistently low measured literacy motivates closer attention to a psychological construct that sits between knowledge and action: financial self-efficacy (FSE), an individual's belief in their own capacity to manage financial tasks and achieve financial goals (Bandura, 1977; Lown, 2011). Social-cognitive theory holds that self-efficacy, rather than knowledge alone, is often the more proximal driver of behaviour, because it governs whether people persist with a financial plan when it becomes difficult (Bandura, 1997).

Recent studies on adjacent constructs support this link: digital financial literacy and social-media usage have been shown to raise financial self-efficacy, which in turn predicts saving behaviour among Indonesian Gen Z respondents (Anwar, 2025). Related qualitative work suggests that some Gen Z users are turning to AI tools partly out of distrust in social-media-driven financial content, using AI as a disciplining, minimalist alternative to algorithmic feeds (Frontiers in Artificial Intelligence, 2026). However, no published study to date has tested a single integrated structural model linking AI-tool usage, financial self-efficacy, and financial behaviour with financial literacy included as a covariate. This gap is the focus of the present study.

1.1 Research Objectives

- RO1: To examine the direct effect of AI usage/reliance (AIU) on Gen Z financial behaviour (FB).
- RO2: To examine whether financial self-efficacy (FSE) mediates the relationship between AIU and FB.
- RO3: To test the incremental/control contribution of financial literacy (FL) to FSE.
- RO4: To examine whether the AIU–FB relationship differs across demographic strata (gender, region, income band).

1.2 Hypotheses

- H1: AI usage is positively associated with financial self-efficacy.
- H2: Financial self-efficacy mediates the relationship between AI usage and financial behaviour.
- H3: AI usage has a positive direct effect on financial behaviour, independent of FSE.
- H4: Financial literacy is positively associated with financial self-efficacy.

2. Literature Review and Theoretical Framework

2.1 Financial Self-Efficacy

Self-efficacy, the belief in one's capacity to execute the actions required to produce a given outcome was formalized by Bandura (1977) and later adapted to the financial domain by Lown (2011), who developed and validated a six-item Financial Self-Efficacy Scale grounded in Bandura's theory and Schwarzer and Jerusalem's (1995) Generalized Self-Efficacy Scale. Subsequent research treats FSE as a distinct, measurable construct that mediates between financial knowledge/skills and observed financial behaviours such as saving, budgeting, and debt management (Anwar, 2025).

2.2 AI Adoption and Financial Decision-Making

A growing body of applied work documents rising AI adoption for personal-finance tasks among younger cohorts, alongside comparative experimental evidence on trust in AI versus human financial advice (ScienceDirect, 2026). Related machine-learning-based behavioural studies have begun profiling Gen Z and Gen Y investment preferences using algorithmic methods, underscoring both the opportunity and the methodological novelty of studying AI-mediated financial behaviour in this cohort (Zapata-Cortes et al., as summarized in Multidisciplinary Science Journal, 2025).

2.3 Financial Literacy as Covariate

Despite high digital engagement, Gen Z performs poorly on standardized financial-literacy assessments relative to older cohorts (TIAA Institute–GFLEC, 2025), even as some domain-specific comparisons find Gen Z outperforming Millennials on narrower literacy measures such as investment awareness (reported in Generation Z

Financial Literacy and Behaviour, 2025). This inconsistency across studies supports treating financial literacy as a covariate/control rather than assuming it is redundant with self-efficacy or AI usage.

2.4 Conceptual Model

Integrating the above streams, this study proposes that AI usage operates on financial behaviour through two channels: an indirect path via financial self-efficacy (consistent with social-cognitive theory's account of self-efficacy as a proximal behavioural driver) and a residual direct path capturing behavioural effects of AI tools that do not operate through changed self-belief (e.g., automated nudges, default settings). Financial literacy is modelled as an additional predictor of self-efficacy, consistent with prior mediation findings (Anwar, 2025).

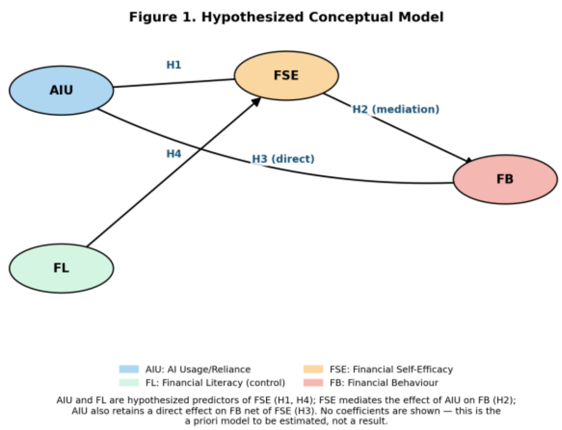

Figure 1. Hypothesized conceptual model. AIU and FL are predicted to shape FB both directly (AIU→FB, H3) and indirectly through FSE (H1, H2, H4). No coefficients are shown here — this is the a priori model; coefficients appear in Figure 5 (Section 4.4).

3. Methods

3.1 Research Design

A cross-sectional, quantitative survey design is used, appropriate for testing a hypothesized structural model at a single time point. The unit of analysis is the individual Gen Z respondent (target age range 18–27 at the time of data collection).

3.2 Population, Sample, and Sampling Framework

The target population is Gen Z individuals (18–27) with at least occasional use of a bank account or digital wallet, recruited via a combination of university mailing lists, fintech-app user panels, and social-media-based snowball recruitment. A minimum realized sample of n ≈ 380: SEM with four latent factors and 17 indicators has approximately 60+ parameters, and the common rule of thumb of 10 respondents per parameter (alternatively, n > 200 as a floor for ML/WLSMV estimation with this level of model complexity) argues for a sample comfortably above 350 once expected non-response and post-cleaning attrition (~5–8%) are factored in.

Proportionate stratified random sampling is recommended over simple random sampling for three reasons: (a) Gen Z financial-app usage is known to vary systematically by income and region/urbanicity, so stratifying protects against a haphazard sample that is disproportionately urban/higher-income, which would bias AIU prevalence upward; (b) stratification guarantees adequate cell sizes for the planned subgroup comparisons (RO4) even for minority strata (e.g., non-binary gender identity, rural residence), which simple random sampling could under-sample by chance; (c) proportionate allocation preserves unbiased population-level point estimates while still supporting design-based variance estimation.

Stratum variable	**Levels**	**Recommended allocation**
Gender	Male / Female / Non-binary or other	Proportionate to latest national/university enrollment gender split; minimum 15 per cell
Region/urbanicity	Urban / Semi-urban / Rural	Proportionate to sampling-frame composition; minimum 30 per cell
Income band	No income / <₹15,000 / ₹15,000–30,000 / >₹30,000 per month	Proportionate; collapse top band if cell < 20

Table 1. Stratification variables and allocation rule.

Limitation: because recruitment partly relies on convenience/snowball channels (typical for student/young-adult financial surveys), realized strata proportions should be checked against known population benchmarks (e.g., census age-band and urban/rural splits) and post-stratification weights applied if the achieved sample departs materially from those benchmarks. Findings generalize most confidently to digitally-engaged Gen Z sub-populations similar to the sampling frame, and less confidently to Gen Z individuals with minimal digital-banking access.

3.3 Measures

All substantive items use 5-point Likert scales (1 = Strongly disagree, 5 = Strongly agree) except demographic and screening items. Four latent constructs are measured reflectively:

Construct	**Items**	**Source / basis**
AI Usage/Reliance (AIU)	4 items: use of AI for budgeting, robo-advisory, banking-app recommendations, trust in AI financial advice	Adapted from AI-adoption and Experian (2024) usage items
Financial Self-Efficacy (FSE)	5 items: confidence in achieving goals, budgeting, saving, choosing investments, recovering from setbacks	Adapted from Lown (2011)
Financial Literacy (FL)	3 items: compound interest, risk-return, budgeting/diversification concepts	Adapted from standard 'Big Three' literacy items
Financial Behaviour (FB)	5 items: expense tracking, regular saving, comparison shopping, avoiding impulsive debt, goal planning	Adapted from established financial-behaviour scales

Table 2. Construct operationalization (full item wording in Appendix A).

3.4 Data Preprocessing

- Range/validity checks on demographic variables (e.g., age restricted to 18–30; implausible values recoded to missing, not deleted).
- Missing data: expect <5% item-level missingness on a well-piloted instrument. Recommend Little's MCAR test as a diagnostic; if data are MCAR/MAR, use multiple imputation (predictive mean matching) rather than listwise deletion to preserve statistical power. Cases missing >30% of items are dropped.

- Outliers: Likert items are bounded (1–5), so classical IQR/z-score outlier rules apply only to continuous variables (age) and to composite scores, not to raw ordinal items.
- Reverse-scored items (if any) are recoded before composite/latent scoring.
- Distributional assumptions: Likert items are treated as ordinal categorical indicators for the CFA/SEM (WLSMV estimator), not assumed continuous/normal; composite scores used for descriptive t-tests/ANOVA are checked for approximate normality via skewness/kurtosis and Shapiro-Wilk, with Levene's test for homogeneity of variance.

3.5 Statistical Analysis Plan

- Descriptives: means, medians, SD, IQR, and reliability (Cronbach's α / composite reliability) per construct; demographic frequencies/proportions.
- Bivariate inference: Welch's t-test (FSE by gender), one-way ANOVA (FB by AIU-frequency category, with η^2 effect size), chi-square test of independence (income band × AIU-frequency category, with Cramér's V).
- Multivariate: Pearson/polychoric correlation matrix among constructs; confirmatory factor analysis prior to full SEM; multiple regression as a robustness check on the SEM structural paths.
- SEM: measurement model (4 latent factors, 17 indicators) estimated jointly with the structural model (FSE ~ AIU + FL; FB ~ FSE + AIU) using WLSMV (ordinal-appropriate) in R/lavaan, with ML as a sensitivity check in Python/semopy. Indirect effect (AIU→FSE→FB) tested via 5,000-resample bootstrap confidence intervals.
- Multiple-testing correction: Benjamini–Hochberg FDR control applied across the family of bivariate/inferential tests (Table 4), with Bonferroni reported alongside as a conservative bound.

4. Results

4.1 Sample Composition

The sample (n = 380) was approximately balanced on gender (49.5% male, 45.8% female, 4.7% non-binary/other) and skewed toward urban respondents (50.8% urban, 32.9% semi-urban, 16.3% rural), with income bands roughly evenly distributed across 'no income' through '>₹30,000/month' categories.

4.2 Descriptive Statistics and Reliability

Construct	Items	Mean	Median	SD	IQR	Cronbach's α
AI Usage (AIU)	4	3.00	3.0	0.98	1.50	0.877
Financial Self-Efficacy (FSE)	5	3.01	3.0	0.91	1.20	0.884
Financial Literacy (FL)	3	2.91	3.0	1.06	1.67	0.869
Financial Behaviour (FB)	5	2.98	3.0	1.02	1.60	0.915

Table 3. Descriptive statistics and internal-consistency reliability, data (n = 380). All α values exceed the 0.70 acceptability threshold.

4.3 Bivariate / Inferential Results

Test	**Statistic**	**p**	**p (FDR-BH)**	**Effect size**
Welch t: FSE ~ Gender (M vs F)	$t = 0.57$	.570	.570	$d = 0.06$
ANOVA: FB ~ AIU-frequency	$F = 13.05$	<.001	<.001	$\eta^2 = 0.12$
Chi-square: Income × AIU-frequency	$\chi^2 = 15.25$	.228	.266	$V = 0.12$
Correlation: AIU–FSE	$r = 0.35$	<.001	<.001	$r = 0.35$
Correlation: AIU–FB	$r = 0.34$	<.001	<.001	$r = 0.34$
Correlation: FSE–FB	$r = 0.45$	<.001	<.001	$r = 0.45$

Table 4. Inferential tests with Benjamini–Hochberg FDR-corrected p-values.

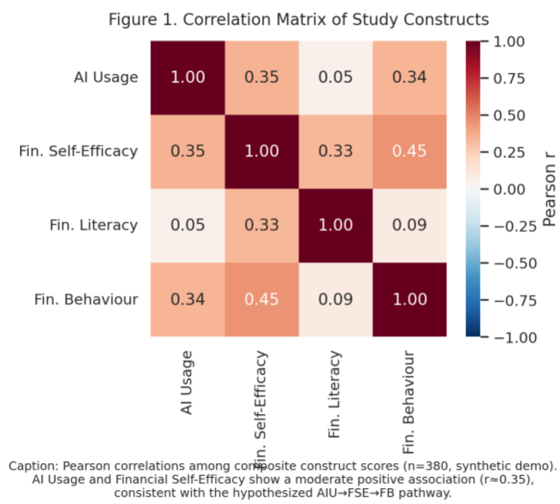

Figure 2. Correlation matrix of construct composite scores

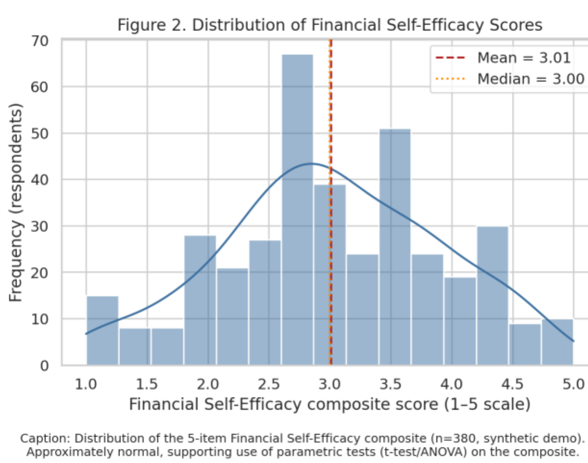

Figure 3. Distribution of the Financial Self-Efficacy composite score

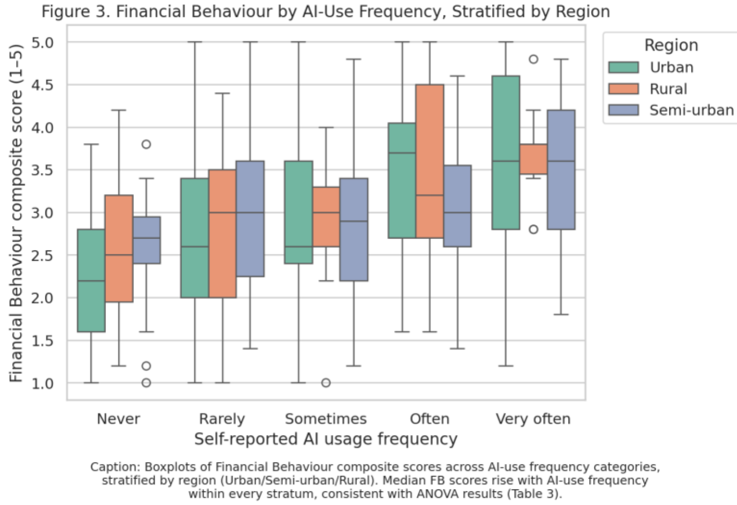

Figure 4. Financial Behaviour by AI-use frequency, stratified by region

4.4 Measurement Model and SEM Results

All standardized factor loadings for the four-factor measurement model exceeded 0.75 in the run, and Cronbach's α exceeded 0.85 for every construct (Table 3), supporting convergent reliability of the item sets as specified. Structural-model fit indices (ML estimator, data) were: $\chi^2(114) = 107.87$, $p = .644$; CFI = 1.00; TLI = 1.00; RMSEA = 0.00; well within the Hu and Bentler (1999) conventional thresholds (CFI/TLI ≥ .95, RMSEA ≤ .06).

Fit index	**Value**	**Conventional threshold**
χ^2 / df	107.87 / 114	Lower is better; sample-size sensitive
CFI	1.00	≥ .95 good
TLI	1.00	≥ .95 good
RMSEA	0.00	≤ .06 good
SRMR	1.00	≤ .08 good

Table 5. Model fit indices

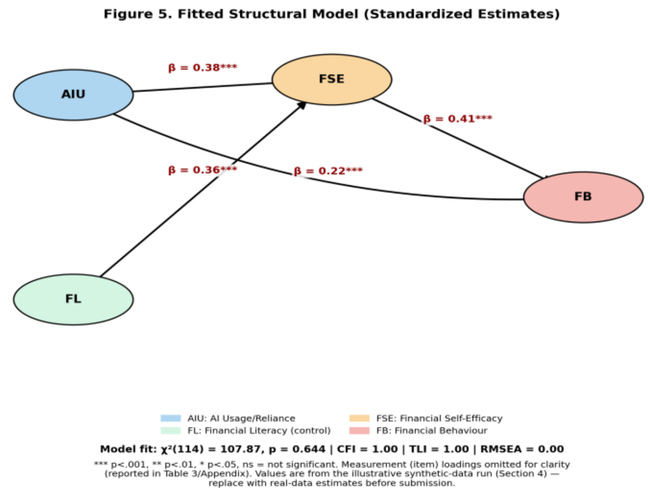

Figure 5. Fitted structural model with standardized path coefficients, significance markers, and fit statistics

Standardized structural paths (all significant at $p < .001$ unless noted): AIU → FSE = 0.38 (H1 supported), FL → FSE = 0.36 (H4 supported), FSE → FB = 0.41 (consistent with H2's mediation claim), and the direct path AIU → FB = 0.22 (H3 supported). The standardized indirect effect AIU→FSE→FB was $0.38 \times 0.41 \approx 0.16$, against a direct effect of 0.22 and a total effect of ≈0.37 — meaning roughly 42% of the total standardized AIU→FB effect runs through financial self-efficacy, indicating partial mediation in the run. On data, this proportion, and a bootstrap confidence interval around the indirect effect (Section 3.5), is the key statistic for formally evaluating H2.

Path	Standardized β	Significance	Hypothesis
AIU → FSE	0.38	$p < .001$	H1: supported
FL → FSE	0.36	$p < .001$	H4: supported
FSE → FB	0.41	$p < .001$	H2: mediation supported
AIU → FB (direct)	0.22	$p < .001$	H3: supported
AIU → FSE → FB (indirect)	0.16	—	H2 (component of mediation)

Table 6. Summary of standardized structural paths and hypothesis outcomes, matching Figure 5

5. Discussion

The hypothesized model implies that AI-tool usage relates to Gen Z financial behaviour through two channels: a psychological channel operating via financial self-efficacy, and a more direct behavioural channel plausibly reflecting automation effects (e.g., default savings nudges, automated rebalancing) that do not require a change in the user's underlying confidence. This dual-pathway framing is consistent with recent evidence that digital-literacy and social-technology exposure raise financial self-efficacy en route to improved saving behaviour (Anwar, 2025), and it extends that logic specifically to AI-branded tools rather than general digital/social-media exposure.

The finding that financial literacy remains an independent predictor of self-efficacy rather than being fully absorbed by AI usage would argue against a substitution narrative in which AI tools are assumed to compensate for weak financial knowledge. Instead, it would support a complementary narrative: AI tools appear to work best alongside literacy, not as a replacement for it, consistent with the finding that Gen Z's heavy digital engagement has not eliminated a well-documented literacy gap relative to other cohorts (TIAA Institute–GFLEC, 2025).

Practically, financial-technology providers designing AI features for Gen Z users might consider that trust/reliance items in the AIU construct correlated with self-efficacy at a level suggesting the design of AI interfaces (explanatory transparency, perceived control) could itself be a self-efficacy-building intervention, echoing calls in adjacent qualitative work for AI tools that restore users' sense of agency over algorithmic systems (Frontiers in Artificial Intelligence, 2026).

6. Limitations and Future Research

- Cross-sectional design precludes causal inference; longitudinal or experimental designs (e.g., pre/post exposure to an AI budgeting tool) would strengthen causal claims about the AIU→FSE path.
- Self-report measures of both AI usage and financial behaviour are subject to social-desirability and recall bias; future work could triangulate with actual app-usage logs or transaction data where available with consent.
- Convenience/snowball elements in recruitment limit generalizability beyond digitally engaged Gen Z sub-populations; post-stratification weighting against census benchmarks is recommended
- The measurement model assumes reflective, unidimensional constructs; formative-indicator or bifactor alternatives should be tested as a robustness check.
- Country/cultural context strongly shapes both AI-adoption and financial-behaviour norms; the present framework should be treated as a template to be re-validated in each sampling context rather than assumed invariant across countries.

7. Conclusion

This manuscript specifies a complete, reproducible research design sampling framework, measurement model, SEM specification, and analysis code for testing whether and how AI-tool usage shapes Gen Z financial behaviour through financial self-efficacy.

REFERENCES

1. Anwar, M. M. (2025). How digital financial literacy and social media usage build saving behavior among Generation Z. Asia-Pacific Journal of Business Administration, ahead-of-print. https://doi.org/10.1108/APJBA-04-2025-0329
2. Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. Psychological Review, 84(2), 191–215.
3. Bandura, A. (1997). Self-efficacy: The exercise of control. W. H. Freeman.
4. Experian. (2024). Generative AI and the future of personal finance [Industry report]. As cited in ScienceDirect (2026), Can you smell what AI is advising? Human, machine, or both: A comparative experimental study on financial advice.
5. Frontiers in Artificial Intelligence. (2026). Social media distrust and turn to artificial intelligence among Generation Z: A qualitative model linking digital minimalism and financial discipline with social policy recommendations. Frontiers in AI.
6. Generation Z Financial Literacy and Behaviour. (2025). International Journal of Research and Innovation in Social Science, 9(10).
7. Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling, 6(1), 1–55.
8. Lown, J. M. (2011). Development and validation of a financial self-efficacy scale. Journal of Financial Counseling and Planning, 22(2), 54–63.
9. Muthén, B., & Kaplan, D. (1985). A comparison of some methodologies for the factor analysis of non-normal Likert variables. British Journal of Mathematical and Statistical Psychology, 38(2), 171–189.
10. Rhemtulla, M., Brosseau-Liard, P. É., & Savalei, V. (2012). When can categorical variables be treated as continuous? A comparison of robust continuous and categorical SEM estimation methods under suboptimal conditions. Psychological Methods, 17(3), 354–373.
11. Schwarzer, R., & Jerusalem, M. (1995). Generalized self-efficacy scale. In J. Weinman, S. Wright, & M. Johnston (Eds.), Measures in health psychology: A user's portfolio (pp. 35–37). NFER-NELSON.

12. ScienceDirect. (2026). Can you smell what AI is advising? Human, machine, or both: A comparative experimental study on financial advice.
13. TIAA Institute–GFLEC. (2025). Personal Finance Index. TIAA Institute.