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Research Article

Economic Knowledge and Financial Management Practices: Self-Efficacy and AI-Supported Learning Engagement

Suchi Fitri Yani* and Anna Kotova

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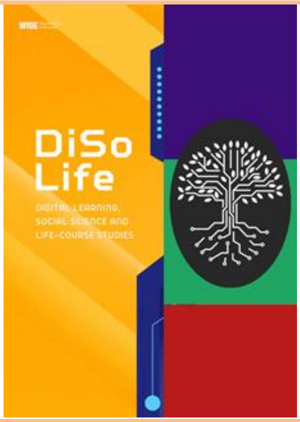
Abstract

Economic knowledge is widely regarded as a foundation for responsible financial behaviour, yet conceptual understanding does not necessarily translate into routine financial practice. This study examined whether economic concept knowledge was associated with everyday financial management practices among 312 undergraduate students in an AI-supported learning context, while evaluating financial self-efficacy as an indirect pathway and AI-supported learning engagement as a boundary condition. A quantitative predictive-correlational design was analysed using multiple regression, percentile-bootstrap indirect-effect estimation, and interaction analysis. Economic concept knowledge was positively associated with financial management practices ($\beta = .435$, $p < .001$), with the baseline model explaining 19.1% of outcome variance. A positive indirect association through financial self-efficacy was supported (indirect $\beta = .115$, 95% CI [.069, .172]), while the direct knowledge association remained significant. AI-supported learning engagement modestly strengthened the knowledge-practice association ($\beta = .094$, $p = .047$), and the final model explained 29.0% of variance. The findings are consistent with an account in which conceptual knowledge is more likely to be reflected in everyday practice when learners also report confidence to act and engage with AI-supported learning in an active, evaluative manner. The results motivate further longitudinal and experimental testing of financial-learning designs that combine conceptual reasoning, self-efficacy, and accountable AI use.

Keywords: financial capability; financial self-efficacy; AI-supported learning; knowledge transfer; financial literacy



INTRODUCTION

Financial decision making has become increasingly demanding for young adults who must interpret inflation, interest, credit costs, savings trade-offs, risk, and digital-payment information while moving toward greater financial independence. International assessments continue to show substantial variation in financial literacy and capability, even as digital financial services increase the speed, accessibility, and complexity of everyday choices [1]-[3]. This problem is educational as well as economic. University students are expected to convert concepts learned in formal or informal learning environments into repeated decisions about spending, saving, borrowing, and planning. Financial literacy is therefore better understood as an applied capability than as the possession of isolated factual knowledge [4], [5].

Evidence supports the importance of financial knowledge, but it also shows that knowledge alone is an incomplete explanation of behaviour. Financial education can improve both knowledge and downstream outcomes, particularly when instruction is timely, targeted, and connected with actual decisions [6]. Objective and perceived financial knowledge are associated with saving, investment, and borrowing behaviours [7], [8], yet meta-analytic and behavioural evidence has repeatedly cautioned against assuming that learning gains automatically become durable practice [9]. The key issue is thus not simply whether students know economic concepts, but how that knowledge becomes actionable when they encounter financial choices outside the learning setting.

Financial self-efficacy provides a theoretically plausible mechanism for this knowledge-to-practice transition. Social-cognitive theory proposes that perceived capability influences whether individuals initiate action, persist when tasks become difficult, and regulate their strategies [10]. In the financial domain, perceived control and confidence are closely connected with well-being and behavioural functioning [11]. A student may understand compound interest or credit costs yet still postpone comparison, budgeting, or repayment decisions when those tasks feel difficult or uncertain. Conversely, stronger conceptual understanding can increase the sense that financial problems are interpretable and manageable. Testing self-efficacy as a mediator therefore helps distinguish possessing economic knowledge from having sufficient confidence to use it.

This transfer problem now intersects with the rapid growth of artificial intelligence in higher education. Human-AI learning research increasingly treats AI as one component of a broader learning system in which learner goals, task design, feedback, verification, and human judgement shape the value of technological support [12]. Generative AI can provide explanations, examples, comparisons, and immediate feedback, but it can also encourage overreliance, superficial acceptance, or inaccurate reasoning when learners lack disciplinary judgement [13]. Reviews of AI in higher education similarly show that educational value depends on pedagogy, learner agency, and the quality of engagement rather than on access alone [14], [15]. Recent empirical and conceptual work further indicates that generative-AI support can alter self-regulated learning processes and that meaningful engagement varies in frequency, inquiry quality, and epistemic agency [35]-[38]. Contemporary guidance has therefore emphasized critical verification, purposeful prompting, and human oversight [16]-[20].

For financial learning, the distinction between AI access and AI-supported learning engagement is especially important. In this study, engagement is conceptualized as the reported quality of cognitive and metacognitive interaction with AI-supported learning rather than simple frequency of tool use. Learners may accept an AI response with little evaluation, or they may request alternative explanations, compare assumptions, seek counterexamples, check calculations, and revise their reasoning; these behaviours represent a continuum of increasingly evaluative engagement rather than a strict active-passive binary. Such engagement is consistent with human-centred AI learning, self-regulated monitoring, and epistemic agency [18]-[22], [35]-[38]. From a transfer perspective, elaboration, comparison, self-explanation, and verification can help learners recognize when economic principles apply in new contexts [23], [24]. Higher-quality AI-supported engagement may therefore strengthen the association between economic knowledge and everyday financial practice without implying that AI use itself causes better financial behaviour.

Despite evidence linking financial knowledge with behaviour and the rapid expansion of AI-supported learning, the two literatures rarely converge around downstream transfer into everyday financial practice. Financial-literacy research often estimates direct knowledge-behaviour relationships without simultaneously examining a proximal self-belief pathway, whereas AI-in-education research has concentrated largely on academic performance, perceptions, and policy rather than life-course-relevant financial routines. What remains unclear is whether financial self-efficacy accounts for part of the observed knowledge-practice association and whether the quality of AI-supported learning engagement conditions its strength. H1 therefore predicts that economic concept knowledge is positively associated with everyday financial management practices after adjustment for age, gender, household-resource level, and prior finance coursework. H2 predicts a positive indirect association between knowledge and practice through financial self-efficacy. H3 predicts that AI-supported learning engagement strengthens the association between economic knowledge and financial management practices. The contribution is an integrated explanatory model that connects financial capability, social-cognitive processes, transfer of learning, and human-AI engagement around an everyday behavioural outcome.

The remainder of the article describes the predictive-correlational design and measures, presents the direct, indirect, and conditional associations together with their interpretation, and concludes with implications and evidentiary boundaries for financial education and AI-supported learning design.

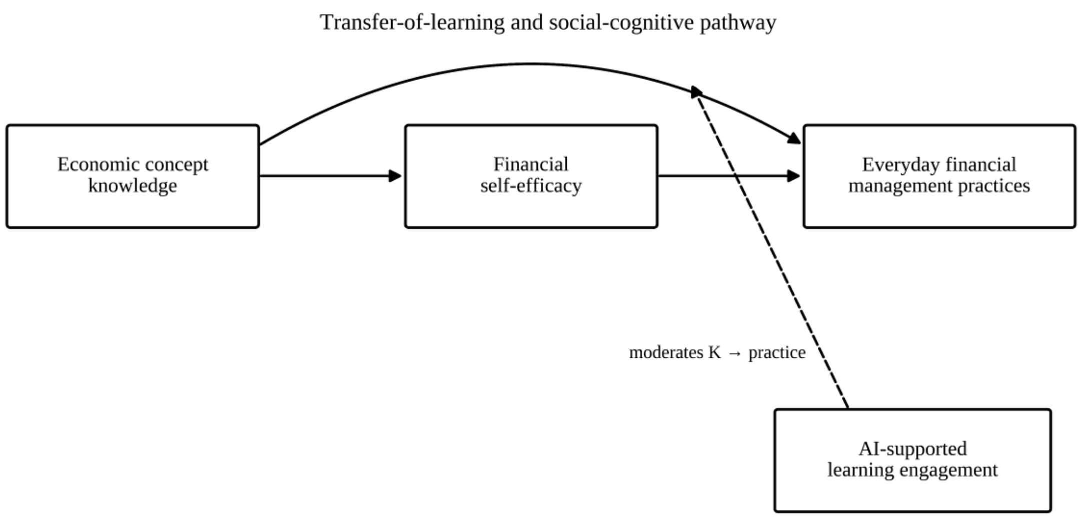


Figure 1. Conceptual framework linking economic knowledge, financial self-efficacy, AI-supported engagement, and financial management practices

Note. Solid arrows represent the proposed direct and indirect statistical pathways; the dashed path indicates moderation of the knowledge-to-practice association by AI-supported learning engagement. Covariates are omitted for readability. Arrows represent hypothesized associations and do not imply temporal or causal effects.

METHODS

Research Design

This study used a quantitative predictive-correlational design to examine direct, indirect, and interaction associations among economic concept knowledge, financial self-efficacy, AI-supported learning engagement, and everyday financial management practices. No instructional condition was manipulated. The design was therefore nonexperimental, and the focal variables were analysed within the same observational dataset without an experimentally established temporal sequence. Regression coefficients, indirect effects, and interactions are consequently interpreted as conditional association patterns rather than causal effects or verified mechanisms. The three hypotheses were evaluated within a common analytic framework so that the knowledge-practice association, the self-efficacy pathway, and the AI-engagement boundary condition could be compared directly.

Participants and Learning Context

The analytic sample comprised 312 undergraduate students. Mean age was 20.7 years (SD = 1.7; range = 18-26); 61.9% were women, and 32.7% had completed prior finance coursework. Socioeconomic variation was represented by a standardized household-resource indicator included as a covariate. The AI-supported learning context refers to undergraduate settings in which AI tools were available to support explanations, worked examples, comparison of alternatives, and formative feedback; the study did not manipulate a standardized AI intervention or test the effect of a particular AI platform. All 312 cases contained complete information for the focal variables and covariates used in the reported models. The sample is therefore treated as the analytic cohort for this study rather than as a nationally or institutionally representative population.

Measures and Instruments

Economic concept knowledge was represented by an objective 0-100 score covering inflation, interest, opportunity cost, diversification, credit cost, and intertemporal choice. Financial self-efficacy, AI-supported learning engagement, and everyday financial management practices were represented by composite 1-5 scale scores. The AI-supported learning engagement construct indexed the reported quality of engagement with AI for explanation, comparison, assumption checking, counterexample seeking, calculation checking, and revision rather than the frequency of access or verified platform activity. Internal consistency was acceptable for all focal measures: KR-20 = .86 for economic concept knowledge, α = .91 for financial self-efficacy, α = .88 for AI-supported learning engagement, and α = .89 for financial management practices. These coefficients document internal consistency in the analytic sample but should not be interpreted as complete evidence of construct validity. Descriptive properties are reported in Table 1.

Table 1. Descriptive statistics and reliability estimates

Measure	M	SD	Observed range	Reliability	Scale
Economic concept knowledge	71.16	10.43	39.26-98.00	KR-20 = .86	0-100

AI-supported learning engagement	3.25	0.62	1.25-4.80	α = .88	1-5
Financial self-efficacy	3.55	0.57	2.08-5.00	α = .91	1-5
Financial management practices	3.45	0.55	1.70-5.00	α = .89	1-5

Note. M and SD are based on observed study scores. Reliability coefficients report internal consistency in the analytic sample and do not, by themselves, establish construct validity.

Data Structure and Preparation

The analytic dataset linked each participant's economic concept knowledge score, financial self-efficacy, AI-supported learning engagement, financial management practices, age, gender, household-resource indicator, and prior finance coursework status. All 312 cases were complete for the variables used in the reported models. Score distributions and observed ranges were reviewed before modelling. Continuous focal variables were standardized before regression and interaction estimation so that coefficients were expressed on a comparable scale and the interaction term could be interpreted through simple slopes. Because the variables were analysed within one observational dataset, the statistical ordering used for the indirect-effect model should not be interpreted as evidence that one construct was temporally measured before another.

Data Analysis

H1 was tested with multiple linear regression in which financial management practices were regressed on economic concept knowledge while adjusting for age, gender, household resources, and prior finance coursework. H2 was evaluated as an indirect association using the knowledge-to-self-efficacy path and the self-efficacy-to-practice path in the outcome model. The indirect effect was calculated as the product of these paths and evaluated with a 2,000-resample percentile-bootstrap 95% confidence interval. This procedure quantifies an indirect statistical pathway but, given the observational design, does not establish causal or temporal mediation. H3 was tested by adding AI-supported learning engagement and the standardized knowledge × AI-supported learning engagement interaction to the outcome model. Conditional slopes were estimated at low (-1 SD), mean, and high (+1 SD) AI-supported learning engagement. Exact p values are reported when $p \geq .001$, and interpretation emphasizes coefficient magnitude, confidence intervals, and explained variance in addition to significance tests.

Analytical Quality Checks

Residual distributions for the fitted outcome models were approximately symmetric, visual residual patterns showed no obvious departure that would invalidate ordinary least-squares estimation, and no variance inflation factor exceeded 1.4. These diagnostics provide evidence against material multicollinearity and gross residual misspecification in the reported models, although diagnostic adequacy does not eliminate unmeasured confounding or establish causal validity. Because the study is observational, the indirect and moderation results are interpreted as explanatory association patterns rather than causal mechanisms.

RESULTS AND DISCUSSION

Preliminary Relationships

Economic concept knowledge averaged 71.16 (SD = 10.43), AI-supported learning engagement 3.25 (SD = 0.62), financial self-efficacy 3.55 (SD = 0.57), and financial management practices 3.45 (SD = 0.55). Pairwise correlations were positive across all focal variables. Knowledge correlated with financial practices at $r = .427$ and with self-efficacy at $r = .439$; AI-supported learning engagement correlated with knowledge at r = .282, with self-efficacy at r = .263, and with financial practices at r = .214; self-efficacy correlated with financial practices at r = .457. The modest correlations involving AI engagement, relative to the stronger knowledge-self-efficacy and self-efficacy-practice relationships, are consistent with the constructs being related but empirically nonredundant rather than interchangeable measures.

Table 2. Correlations among focal variables

Variable	1	2	3	4
1. Economic concept knowledge	—			
2. AI-supported learning engagement	.282	—		
3. Financial self-efficacy	.439	.263	—	
4. Financial management practices	.427	.214	.457	—

Note. Values are Pearson correlations among standardized focal variables; N = 312.

Economic Knowledge and Financial Practice

The baseline regression supported H1. Economic concept knowledge was positively associated with everyday financial management practices, β = .435, SE = .052, t(306) = 8.40, p < .001, 95% CI [.333, .537]. The model explained 19.1% of the variance in financial management practices, F(5, 306) = 14.49, p < .001, while none of the four control variables reached statistical significance. Thus, greater economic concept knowledge was associated with stronger financial management practice after age, gender, household resources, and prior finance coursework were taken into account. The reported model establishes an adjusted association, not a causal effect of knowledge on behaviour.

This result is consistent with financial-literacy research showing that economic and financial knowledge matters for saving, investment, borrowing, and other consequential decisions [6]-[8], [22], [25], [26]. At the same time, the explained variance indicates that knowledge is important but not deterministic. This distinction is central to modern financial-capability perspectives: knowledge supplies a conceptual resource, whereas behaviour also depends on perceived capability and contextual constraints [3], [4], [11]. From a transfer-of-learning perspective, knowing a definition is not equivalent to recognizing when the underlying principle applies in a new decision. Transfer requires abstraction, comparison, and flexible application across changing surface conditions [23], [24]. These results also align with foundational distinctions between financial knowledge and applied financial literacy [27], [28].

Financial Self-Efficacy as an Indirect Pathway

H2 was supported as a positive indirect association. Economic concept knowledge was positively associated with financial self-efficacy, β = .381, SE = .053, t = 7.26, p < .001, 95% CI [.278, .485]. In the full outcome model, financial self-efficacy remained positively associated with financial management practices, β = .303, SE = .056, t = 5.43, p < .001, 95% CI [.193, .413], while the direct knowledge association remained significant, β = .283, SE = .055, t = 5.11, p < .001, 95% CI [.174, .392]. The bootstrapped indirect effect was β = .115, 95% CI [.069, .172]. Statistically, this pattern is consistent with an indirect pathway alongside a remaining direct association; because temporal precedence was not established, it should not be interpreted as evidence of a causal mediating mechanism.

Table 3. Regression coefficients for baseline, mediator, and full outcome specifications

Outcome / predictor	β	SE	t	p	95% CI
Financial management (baseline): knowledge	.435	.052	8.40	< .001	[.333, .537]
Self-efficacy model: knowledge	.381	.053	7.26	< .001	[.278, .485]
Financial management (full): knowledge	.283	.055	5.11	< .001	[.174, .392]
Financial management (full): self-efficacy	.303	.056	5.43	< .001	[.193, .413]
Financial management (full): AI engagement	.059	.052	1.13	.258	[-.043, .161]
Financial management (full): knowledge × AI	.094	.047	2.00	.047	[.001, .186]

Note. β denotes standardized coefficients. The table reports focal coefficients from the baseline, mediator, and full outcome specifications. Age, gender, household-resource indicator, and prior finance coursework were included as covariates in the financial-management models; none reached statistical significance in the baseline model. The indirect association through self-efficacy was $\beta = .115$, 95% CI [.069, .172].

The indirect pattern is consistent with a theoretically plausible pathway through which knowledge and practice may be connected, rather than a demonstrated causal explanation. Social-cognitive theory predicts that people are more likely to initiate and sustain behaviours when they believe they can execute them successfully [10]. In financial settings, conceptual mastery may reduce perceived complexity and increase confidence, while self-efficacy may support persistence in tasks such as comparing alternatives or maintaining financial routines. The finding therefore complements broader financial-well-being models that distinguish objective resources, subjective appraisal, and behavioural functioning [11]. Educationally, assessments focused only on correct financial answers may overlook a proximal psychological correlate of enacted practice. Nevertheless, reverse or reciprocal ordering and omitted-variable confounding remain plausible in an observational dataset, so the proposed sequence requires longitudinal or experimental confirmation.

AI-Supported Engagement as a Boundary Condition

H3 received modest and tentative support. The knowledge × AI-supported learning engagement interaction was positive, $\beta = .094$, $SE = .047$, $t(303) = 2.00$, $p = .047$, 95% CI [.001, .186]. The final model explained 29.0% of the variance in financial management practices, $F(8, 303) = 15.50$, $p < .001$. Simple-slope analysis showed that the association between knowledge and practice remained positive at low AI engagement (-1 SD), $\beta = .189$, $p = .009$; increased at mean engagement, $\beta = .283$, $p < .001$; and was strongest at high engagement (+1 SD), $\beta = .377$, $p < .001$. Figure 2 illustrates this conditional pattern. Because the interaction is small and its confidence interval approaches zero, its magnitude should be treated as preliminary and replicated before strong substantive conclusions are drawn.

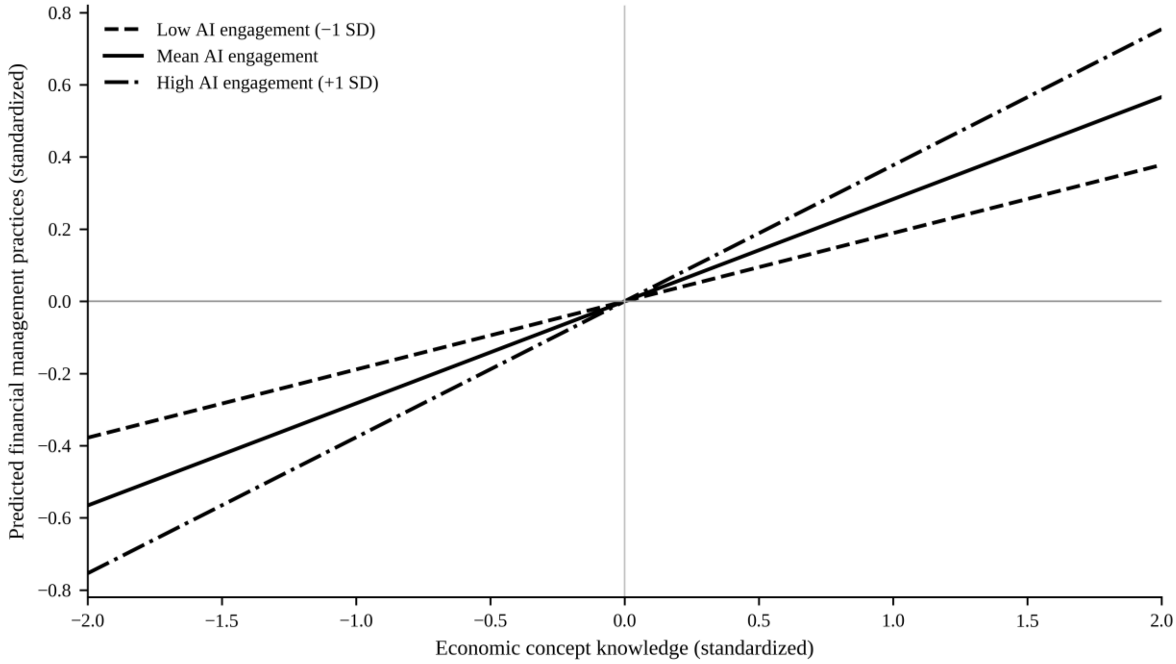


Figure 2. Conditional association between economic concept knowledge and financial management practices

Note. Lines show model-implied simple slopes at low (-1 SD), mean, and high (+1 SD) AI-supported learning engagement. Uncertainty bands are not displayed; uncertainty for the interaction coefficient is reported in the accompanying text.

The moderation effect is small, but its direction is theoretically informative. Generative AI can provide alternative explanations, worked examples, and immediate feedback, yet the educational value of these affordances depends on how learners engage with them [12]-[18]. Broader reviews and conceptual analyses similarly describe both educational opportunity and the risks of overreliance, weak pedagogy, and uncritical acceptance [29]-[32]. Active behaviours such as checking assumptions, requesting comparisons, seeking counterexamples, checking calculations, and revising reasoning require learners to monitor and evaluate rather than merely accept AI output. This pattern is consistent with self-regulated learning, metacognitive monitoring, and human epistemic agency, while recent empirical work also shows that generative-AI engagement differs in depth and inquiry quality and does not reduce to usage frequency [35]-[38]. In the present model, higher-quality AI-supported engagement appears to function as a condition under which economic knowledge is more strongly associated with financial practice. Because the design is correlational and the interaction is modest, however, the result should not be interpreted as evidence that AI use itself improves financial behaviour.

Educational Implications and Study Boundaries

Taken together, the direct, indirect, and moderated results motivate a three-part design principle for further testing in financial learning: develop conceptual understanding, strengthen confidence to act, and structure AI use so that learners remain responsible for verification and decision making. Financial education could operationalize this principle by asking students to justify recommendations, compare alternatives, identify missing information, test assumptions, and translate reasoning into concrete routines. For example, a student could use AI to generate alternative credit or savings scenarios, then independently recompute an interest calculation, identify assumptions omitted from the response, compare the recommendation with a second source, and justify a final decision without relying on the AI output as authority. Such activities position AI as a reflective scaffold rather than a substitute for judgement. Because the present study did not experimentally compare instructional task designs, these recommendations should be treated as pedagogical implications to be evaluated rather than as established intervention effects.

Several boundaries should qualify interpretation. First, the predictive-correlational design does not establish temporal or causal direction among knowledge, self-efficacy, AI engagement, and financial practice; reverse and reciprocal relationships remain possible. Second, financial self-efficacy, AI-supported learning engagement, and financial management practices are composite scale measures, creating potential for shared-method variance and socially desirable responding. Third, omitted variables related to prior financial experience, motivation, digital competence, or contextual opportunity could confound estimated direct and indirect associations. Fourth, the AI-engagement score represents reported quality of engagement rather than verified platform logs, model versions, prompt histories, response quality, or simple frequency of use. Fifth, the study uses one analytic sample, so the findings should not be treated as institutionally or nationally representative without replication across disciplines, socioeconomic conditions, and financial systems. Sixth, the modest interaction coefficient and confidence interval close to zero indicate that the moderation result requires replication. Future research should distinguish frequency of AI use from quality of engagement, validate AI-engagement measures against behavioural traces where feasible, and examine whether structured prompting or verification protocols improve transfer relative to non-AI worked examples. Longitudinal, multi-institutional, and experimental studies would be especially valuable for establishing temporal ordering and testing whether changes in self-efficacy and purposeful AI engagement precede durable changes in financial behaviour.

CONCLUSION

This study examined how economic concept knowledge relates to everyday financial management practices in an AI-supported undergraduate learning context. Economic knowledge was positively associated with financial practice after adjustment for age, gender, household resources, and prior finance coursework. A positive indirect association through financial self-efficacy was observed, while AI-supported learning engagement modestly strengthened the knowledge-practice relationship. The combined model therefore supports an interpretation in which conceptual understanding is important but insufficient on its own to explain observed variation in everyday practice: knowledge is more likely to be accompanied by stronger financial routines when learners also report confidence to act and more evaluative engagement with AI-supported learning. The principal contribution is an integrated explanatory model connecting financial capability, social-cognitive processes, transfer of learning, and human-AI engagement around a life-course-relevant behavioural outcome. The study does not establish that AI use improves financial behaviour or that self-efficacy causally mediates knowledge transfer. For practice, the findings motivate testing financial-learning designs that couple conceptual explanation with decision-confidence building and independent verification of AI-supported reasoning. Longitudinal, multi-institutional, and experimental research using validated behavioural outcomes and verified AI-use indicators is needed to test temporal ordering, causal mechanisms, and durable transfer.

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AUTHOR CONTRIBUTION

S.F.Y. was responsible for the conceptualization, methodology, software development, validation, formal analysis, investigation, data curation, writing the original draft, writing the review and editing, visualization, and project administration. A.K. contributed to the methodology, formal analysis, writing the review and editing, and supervision of the study.

CONFLICT OF INTEREST

The author declares no conflict of interest.

DECLARATION OF USE OF AI IN SCIENTIFIC WRITING

The author used OpenAI ChatGPT during the preparation of this work to support language refinement, structural consistency, and formatting to the journal template. After utilizing the tool, the author thoroughly reviewed and edited the content as necessary and assumes full responsibility for the publication's content.

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