From Pen and Paper to Prompt Engineering: Financial Literacy and AI Integration in Japanese EFL Classrooms

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Abstract

This study examined the effects of a brief, three-session AI-assisted financial literacy intervention on Japanese university students' financial knowledge, saving behavior, and attitudes. The intervention, delivered in mandatory English as a foreign language (EFL) courses at a private university in western Japan, was structured using the AI Assessment Scale (AIAS; Perkins et al., 2024) to guide the progressive integration of generative AI from no AI use to full AI collaboration. Ninety-nine students completed a pre-intervention survey and fifty-five completed a post-intervention survey using the Youth Financial Literacy Short Scale (YFLSS; Potrich et al., 2025), supplemented by measures of perceptions of AI-assisted learning and financial self-efficacy. Independent samples *t* tests revealed no significant pre-post changes in financial knowledge, saving behavior, or financial attitudes. However, post-intervention data indicated that most students perceived AI as beneficial to their learning, with 81.8% reporting effective AI use and 69.1% verifying AI output before application. Financial self-efficacy was moderate to strong for budgeting and emergency fund concepts but substantially lower for specialized knowledge, such as the 4% retirement rule. Thematic analysis of student essays, presentations, and AI interaction logs identified three qualitative themes: localized optimization and problem solving, structural reasoning facilitated by AI as a logic architect, and anxiety reduction through metacognitive awareness. These findings suggest that the primary value of short-term AI-assisted financial literacy interventions may lie in building applied competence, fostering critical engagement with AI, and reducing financial anxiety among young adults, rather than in shifting standardized test scores.

Keywords: financial literacy, generative AI, AI assessment scale, Japanese university students, financial self-efficacy

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Introduction

Historically, Japanese households have favored saving over investing. For decades, a reliable pension system meant that citizens had little incentive to risk their money in pursuit of higher returns. Currently, 51% of Japanese household financial assets are kept in simple savings accounts, while only 19.6% are in bonds, stocks, and funds (Bank of Japan, 2025). However, a series of economic and demographic shifts has begun to change this deeply rooted financial culture. In 2014, as part of an effort to stimulate the economy, the Japanese government introduced the Nippon Individual Savings Account (NISA), a tax-advantaged investment program designed to encourage households to invest rather than keep their money in low-yield bank accounts. In 2019, Japan's Financial System Council reported that retirees need approximately 20 million yen beyond their pension to live comfortably (Financial System Council, 2019), a finding that prompted widespread concern and motivated many citizens to learn about investing for the first time. Since then, awareness of investing has grown. According to the Financial Services Agency (2025), the number of NISA accounts increased 1.2 times between December 2023 and December 2024. The Japan Financial Literacy and Education Corporation (J-FLEC, 2025) reported that the number of securities held by two-person households rose sharply from 481 in 2024 to 755 in 2025, and that preferences for financial products shifted from a focus on security (45% in 2016; 26% in 2025) to profitability (17% in 2016; 41% in 2025). These trends suggest that Japanese households are not only becoming more aware of investing but are actively changing their financial behavior from risk avoidance to asset growth.

Alongside this economic shift, the Japanese government lowered the legal age of adulthood from 20 to 18 in April 2022 (National Diet of Japan, 2018). As a result, 18-year-olds can now sign contracts and obtain loans without parental consent, making young people more vulnerable to financial risks. To address this, the Ministry of Education, Culture, Sports, Science and Technology (MEXT) embedded financial education into the national curriculum starting in April 2022, with high school students learning about financial products, investment, and risk management (Horie & Oyabu, 2021). Despite these policy changes, research on financial literacy among Japanese youth remains limited. Self-reported financial confidence in Japan is considerably lower than in other developed nations, with only 12% of respondents rating their knowledge as high, compared to 71% in the United States (Central Council for Financial Services Information, 2022). This gap between financial awareness and actual literacy underscores the need for effective educational interventions, particularly at the university level.

At the same time, the rapid advancement of generative artificial intelligence (AI) has introduced new possibilities and challenges for education. Research on AI in education has expanded rapidly, with a recent meta-analysis of chatbot-based interventions finding a small but statistically significant positive effect on learning performance across educational contexts (Laun & Wolff, 2025). However, integrating AI into teaching is not without risk. Holmes and Tuomi (2022) noted that while AI allows learners to personalize the system based on their input, the technology is limited in scope and often provides a fixed learning path that may not fully address individual needs. In financial education specifically, Roberts (2023) tested ChatGPT on standardized financial literacy assessments and found that while the AI outperformed most human test-takers, it made unexpected errors on questions involving nuance and quantitative reasoning, leading him to conclude that AI will accelerate progress on financial literacy but cannot replace the need for foundational financial education. Niszczota and Abbas (2023) similarly evaluated GPT models on financial literacy tests and found that

while GPT-3.5 demonstrated limited proficiency, GPT-4 achieved a near-perfect score, suggesting that AI's financial capabilities are improving rapidly but that users still require adequate literacy to interpret and verify AI-generated responses.

One framework that addresses the challenge of integrating AI responsibly into instruction is the AI Assessment Scale (AIAS), developed by Perkins et al. (2024). The AIAS provides a five-level rubric for integrating generative AI into educational assessment, ranging from Level 1 (no AI permitted) through Level 5 (full AI collaboration). Rather than taking a binary allow-or-prohibit approach, the AIAS encourages educators to specify the degree and type of AI engagement appropriate for each task, thereby fostering transparency, ethical use, and the progressive development of AI-related skills. In the present study, the AIAS was adapted from an assessment framework into a pedagogical usage scale to structure the intervention. This adaptation represents an underexplored use of the AIAS: rather than guiding how students are assessed, it guided the sequencing of instruction, with each session corresponding to an increasing level of AI engagement.

Recent research has begun to examine how AI tools can be integrated into financial literacy courses at the university level. Gorham and Mills (2024) found that a 15-week AI-enhanced personal finance course significantly improved students' financial knowledge and behavior, though financial attitudes remained largely unchanged. A follow-up study (Gorham & Mills, 2025) expanded the investigation to three universities and found that students who did not use AI tutors exhibited stronger financial behaviors in some categories, suggesting that instructional design and socioeconomic factors may play a greater role than AI itself. However, research in this area remains limited in several respects. Existing studies have focused primarily on semester-long courses in Western educational contexts, leaving open the question of whether shorter interventions can produce meaningful outcomes. Little research has examined AI-assisted financial literacy instruction in English as a foreign language (EFL) settings, where language proficiency adds an additional layer of complexity. Moreover, the use of the AIAS as a pedagogical sequencing tool, rather than solely as an assessment framework, has not been previously investigated. The present study addresses these gaps.

This study advances existing research by evaluating the effects of a brief, three-session AI-assisted financial literacy intervention on Japanese university students' financial knowledge, saving behavior, and attitudes. In contrast to prior studies that examined semester-long courses, this investigation centers on a short-term intervention delivered in mandatory EFL classes at a private university in western Japan. The intervention was structured using the AI Assessment Scale (AIAS; Perkins et al., 2024), which provided a systematic framework for progressively introducing AI at increasing levels of student engagement. Employing the validated Youth Financial Literacy Short Scale (YFLSS; Potrich et al., 2025) and supplementary measures of perceptions of AI-assisted learning and financial self-efficacy, the study provides a focused quantitative assessment of the outcomes achievable through a brief, structured intervention. Additionally, thematic analysis of student-produced artifacts, including essays, presentation materials, and AI interaction logs, provides qualitative insights into students' engagement with AI tools across AIAS levels and their application of financial planning concepts.

Research Purpose and Questions

This study examined the short-term impact of an AI-assisted financial literacy intervention on Japanese university students' financial knowledge, saving behavior, and attitudes, as well as their perceptions of AI as a learning tool and their financial self-efficacy. It also explored how

students applied financial planning concepts and engaged with AI by analyzing their written and oral coursework, as well as AI interaction logs. The intervention was structured around the AI Assessment Scale (Perkins et al., 2024), which guided the progressive integration of generative AI across three instructional sessions. The following research questions were addressed:

1. What effect does a brief AI-assisted financial literacy intervention have on Japanese university students' financial knowledge, saving behavior, and financial attitudes as measured by the YFLSS?
2. What are Japanese university students' perceptions of using generative AI in a financial literacy learning context?
3. To what extent do students report financial self-efficacy in applying the financial planning concepts covered in the intervention?
4. What themes emerge from students' essays, presentations, and AI interaction logs regarding their engagement with AI tools and application of financial planning concepts across the AIAS levels?

Methodology

Setting and Participants

The study was conducted at a private university in western Japan with approximately 26,800 undergraduate students across 14 faculties. The participants were first-year students enrolled in mandatory intermediate-level EFL courses. Their academic backgrounds varied, with students drawn from the School of Theology and the Faculties of Policy Studies, Letters, Social Studies, and Commerce. All participants were native Japanese speakers. The intervention was implemented across two reading and writing (RW) sections and two listening and speaking (LS) sections over a three-week period, with one 90-minute session per week.

Table 1
Participant Demographics

Characteristic	Pre-survey (*n* = 99)	Post-survey (*n* = 55)
Course type		
Reading & Writing	52	28
Listening & Speaking	47	27

Note. All participants were first-year students and native Japanese speakers.

A total of 99 students completed the pre-intervention survey, and 55 completed the post-intervention survey, yielding an attrition rate of 44.4%. The attrition was primarily due to student absences on the day the post-survey was administered during Session 3. Absence rates were roughly proportional across the four sections, with no single section accounting for a disproportionate share of missing respondents. Because the post-survey was administered only at the end of the final session, students who were absent for any reason, including illness, scheduling conflicts, or other commitments, were not captured. This level of attrition is a methodological limitation, as it raises the possibility that the post-survey sample may differ systematically from the pre-survey sample (e.g., if less motivated or lower-performing students were disproportionately absent). This issue is addressed further in the Conclusion. The study

received ethical approval from the university, and informed consent was obtained from all participants prior to data collection.

Classroom Procedures

The intervention was implemented over three consecutive weekly sessions, each structured using an adapted version of the AI Assessment Scale (AIAS; Perkins et al., 2024). Rather than serving as an assessment rubric, the AIAS functioned as a pedagogical framework to guide the progressive integration of generative AI into instructional activities. This approach draws on the concept of AI as a cognitive scaffold, in which AI tools extend students' capacity to engage with complex tasks, and the structured progression ensures that foundational understanding is established before reliance on AI. Table 2 provides an overview of the intervention design.

Table 2
Summary of Intervention Design Across AIAS Levels

Session	AIAS Level	Activity	AI Use
1	Level 1 (No AI)	Financial planning worksheet with example case; guided calculation tasks	None
2	Levels 2–3 (AI-Assisted)	New case; complete financial plan with AI support; AI feedback on drafts	AI for calculations, scenarios, feedback
3	Levels 4–5 (Full Collaboration)	Summative task: group presentations (LS) or individual reports (RW)	Full AI collaboration; critical evaluation required

Note. LS = Listening and Speaking sections; RW = Reading and Writing sections.

Session 1

In accordance with AIAS Level 1 (No AI), students received direct instruction in foundational financial planning concepts. As most students had little prior exposure to financial planning, the session focused on building a shared knowledge base. The instructor introduced a five-step financial planning process: (a) budgeting, (b) building an emergency fund, (c) planning investments, (d) setting a retirement target, and (e) calculating a possible retirement age. Students were not permitted to use AI tools during this session. Working in groups of three to four, they read an example case and completed a series of guided tasks: adjusting income and expenses to increase monthly savings, calculating an appropriate emergency fund amount, determining how much the persona in the case could invest monthly and as a lump sum, and identifying the persona's target retirement age and the savings needed to reach it. The instructor circulated among groups, observing their processes and explaining unfamiliar terms and calculation methods. All work was completed by hand on paper worksheets.

Session 2

Students were presented with a new example case and tasked with developing a comprehensive financial plan utilizing AI support. Corresponding to AIAS Levels 2–3 (AI-Assisted Ideation and AI-Assisted Editing), various generative AI tools were employed to assist with calculations, explore alternative savings scenarios, and generate recommendations for plan improvement. After completing an initial draft, students submitted their plans to the AI for

feedback and suggestions. They were instructed to critically assess the AI's recommendations and to accept, modify, or reject them in accordance with the financial planning principles introduced in Session 1. This session aimed to provide students with practical experience using AI as a collaborative tool while emphasizing the need for independent judgment when interpreting AI-generated output.

Session 3

Students demonstrated what they had learned through a summative task. In the LS sections, students delivered group presentations in which they explained how they had used AI to improve their assigned financial planning case, describing the changes they made and the reasoning behind their decisions. In the RW sections, students wrote individual reports analyzing the financial plan they had developed, reflecting on the role AI played in the process, and evaluating the quality of the AI's suggestions. In both formats, students were expected to demonstrate not only financial planning knowledge but also critical engagement with AI-generated content.

Quantitative Instrument

The primary quantitative instrument was the Youth Financial Literacy Short Scale (YFLSS; Potrich et al., 2025), a validated measure designed to assess financial literacy among young adults across three dimensions: financial knowledge, saving behavior, and financial attitudes. The YFLSS was selected for its brevity, cross-cultural applicability, and alignment with the intervention's targeted constructs. The instrument was administered in both English and Japanese to accommodate varying levels of English proficiency.

In addition to the YFLSS, the post-intervention survey included two supplementary scales. The first measured students' perceptions of AI-assisted learning, with items addressing the perceived usefulness, ease of use, and trustworthiness of generative AI as a learning tool in the financial literacy context. The second measured financial self-efficacy, with items asking students to rate their confidence in performing specific financial planning tasks covered during the intervention, such as creating a budget, calculating compound interest, and evaluating investment options. Both supplementary scales used a five-point Likert format. Items were developed by the researcher based on the instructional content and reviewed for face validity prior to administration.

Qualitative Artifacts

The qualitative data consisted of three types of student-produced artifacts collected during Session 3. From the RW sections, 51 individual written reports were collected in which students analyzed their financial plans and reflected on their use of AI. From the LS sections, 16 group presentation slide sets, each with accompanying notes, were collected. In addition, 34 AI interaction logs were collected from consenting participants across all sections. In total, 101 artifacts were included in the qualitative analysis. These artifacts provided evidence of how students engaged with AI tools at different AIAS levels and how they applied, adapted, or rejected AI-generated financial planning suggestions.

Data Collection and Analysis

Quantitative data were collected at two time points. The pre-intervention survey, which included the YFLSS and demographic questions, was administered at the beginning of Session 1. The post-intervention survey, which included the YFLSS, the AI-assisted learning perceptions scale, and the financial self-efficacy scale, was administered at the end of Session 3. Surveys were distributed and completed electronically using Google Forms during class time. A total of 99 students completed the pre-survey and 55 completed the post-survey, yielding an attrition rate of 44.4%. Because the surveys were administered anonymously and student identifiers were not collected, individual responses could not be matched across time points. Pre-post comparisons were therefore conducted using independent-samples designs rather than paired-samples tests.

For Research Question 1, independent-samples *t* tests (Welch's) were used to compare pre- and post-intervention scores on the YFLSS dimensions of financial knowledge, saving behavior, and financial attitudes. Effect sizes were calculated using Cohen's d for all major comparisons. Chi-square tests of independence were conducted on individual financial knowledge items to examine item-level changes, and a Mann-Whitney *U* test was used to confirm the parametric findings for the knowledge composite. Internal consistency of the Likert-scale measures was assessed using Cronbach's alpha. Internal consistency was not computed for the dichotomous knowledge items using Cronbach's alpha, as items of varying difficulty violate the assumptions of that statistic; the Kuder-Richardson 20 (KR-20) formula would be more appropriate for such items but was not computed given the small number of knowledge items. For Research Questions 2 and 3, descriptive statistics (means, standard deviations, and percentage distributions) were computed for the AI-assisted learning perceptions and financial self-efficacy scales, respectively, both of which were administered only in the post-survey. Pearson correlations were computed to explore relationships among post-intervention measures.

All statistical analyses were conducted using SPSS version 31. Preliminary calculations were also performed using AI-assisted statistical tools (Gemini and Claude) for initial data exploration and descriptive-statistics verification, but all final results reported in this paper were confirmed using SPSS.

For Research Question 4, the qualitative artifacts were analyzed using reflexive thematic analysis following the six-phase approach described by Braun and Clarke (2006). The researcher, who was also the course instructor, first read all 101 artifacts to become familiar with the data, then generated initial codes related to students' engagement with AI and the application of financial planning concepts. Codes were organized into candidate themes, which were reviewed and refined through iterative re-reading of the data. Because the analysis was conducted by a single researcher, a reflexive approach was adopted in which the researcher maintained an audit trail of coding decisions and revisited earlier coding as new themes emerged. The analysis specifically examined patterns across the AIAS levels, focusing on how the nature and depth of student engagement with AI shifted from Session 1 (no AI) to Sessions 2 and 3 (progressively greater AI involvement). Representative excerpts from student essays, presentation notes, and AI interaction logs were selected to illustrate each theme.

Results

Research Question 1: Financial Knowledge, Saving Behavior, and Attitudes

Research Question 1 asked what effect a brief AI-assisted financial literacy intervention has on Japanese university students' financial knowledge, saving behavior, and financial attitudes as measured by the YFLSS. Because the surveys were administered anonymously and respondents could not be matched across time points, pre-post comparisons were conducted using independent-samples tests.

Financial Knowledge

Financial knowledge was assessed using five items covering compound interest, stock diversification, discount calculation, inflation, and interest computation. Each item was scored dichotomously (1 = correct, 0 = incorrect), yielding a composite score ranging from 0 to 5. Internal consistency was not computed for the knowledge scale using Cronbach's alpha, as dichotomous items of varying difficulty do not meet the assumptions of that statistic; the Kuder-Richardson 20 (KR-20) coefficient would be the appropriate reliability measure for such items but was not computed given the limited number of items.

As shown in Table 3, overall financial knowledge scores were virtually identical between the pre-survey (M = 3.92, SD = 1.39) and post-survey (M = 3.91, SD = 1.46), and the difference was not statistically significant, $t(152) = 0.042$, $p = .966$, Cohen's $d = 0.007$. Chi-square tests on individual items similarly revealed no significant pre-post differences. The item on stock diversification showed the largest numerical increase (from 65.7% to 74.5%), but this difference did not reach statistical significance, $\chi^2(1) = 1.302$, $p = .254$. Both the discount calculation item (87.9% and 87.3%) and the compound interest item (79.8% and 78.2%) showed high accuracy and remained stable. A Mann-Whitney U test confirmed the parametric results ($U = 2664.5$, $p = .817$).

Table 3
Financial Knowledge Item Performance: Pre- vs. Post-survey

Knowledge Item	Pre % Correct	Post % Correct	χ^2	p
Q1: Compound interest	79.8	78.2	0.056	.813
Q2: Stock diversification	65.7	74.5	1.302	.254
Q3: Discount calculation	87.9	87.3	0.012	.913
Q4: Inflation impact	69.7	67.3	0.097	.756
Q5: Interest calculation	88.9	83.6	0.863	.353
Total (*M* out of 5)	3.92 (1.39)	3.91 (1.46)	$t = 0.042$	.966

Note. SD in parentheses for the total score row. Pre $n = 99$; Post $n = 55$. Cohen's $d = 0.007$.

Saving Behavior

Saving behavior was measured using seven Likert-scale items (1 = Never to 5 = Always for frequency items; 1 = Strongly Agree to 5 = Strongly Disagree for attitudinal items). The five positively-worded frequency items demonstrated good internal consistency in both the pre-survey (α = .837) and post-survey (α = .821).

As presented in Table 4, no significant pre-post differences were found on any individual saving behavior item or on the composite score of the five frequency items (pre M = 3.08, SD = 0.96; post M = 2.98, SD = 0.90), $t(152) = 0.59$, p = .555, Cohen's d = 0.11. The two attitudinal items regarding spending orientation also showed no significant change across time points. These results indicate that the brief intervention did not measurably alter students' self-reported saving behaviors or spending attitudes.

Table 4
Saving Behavior Items: Pre- vs. Post-survey Comparisons

Saving Behavior Item	Pre *M*	Pre *SD*	Post *M*	Post *SD*	*t*	*p*
Reserve money for future	3.34	1.12	3.16	1.03	0.94	.347
Keep part of income monthly	3.31	1.26	3.25	1.21	0.28	.779
Save for long-term goals	2.29	1.17	2.20	1.21	0.47	.642
Save more with salary increase	3.09	1.27	3.02	1.16	0.35	.726
Saved money past 12 months	3.31	1.31	3.27	1.30	0.18	.855
Prefer spending over saving*	2.68	0.97	2.53	0.94	0.93	.355
Money is made to spend*	2.03	0.85	2.09	0.89	–0.41	.680
Composite (items 1–5)	3.08	0.96	2.98	0.90	0.59	.555

Note. Scale: 1 = Never/Strongly Agree to 5 = Always/Strongly Disagree. *Attitudinal items; lower scores indicate stronger spending orientation. Pre n = 99; Post n = 55. Cohen's d = 0.11 for the composite.

Research Question 2: Perceptions of AI-Assisted Learning

Research Question 2 asked about Japanese university students' perceptions of using generative AI in a financial literacy learning context. Six items assessed students' perceptions of AI use in the financial literacy instruction (post-survey only; 1 = Strongly Agree to 5 = Strongly Disagree). The five positively-worded items showed acceptable internal consistency (α = .625). While this value is below the conventional threshold of .70, it is not uncommon for short scales with a limited number of items in exploratory research and is considered acceptable for a conference proceedings paper reporting on a newly developed instrument.

As shown in Table 5, students reported broadly favorable attitudes toward the AI-assisted learning experience. The strongest endorsement was for the item on learning to use AI

effectively for academic work, with 81.8% of respondents agreeing or strongly agreeing (M = 2.09, SD = 0.82). A substantial majority also agreed that AI improved group project efficiency (69.1%; M = 2.22, SD = 0.88) and that they felt confident using AI for future assignments (70.9%; M = 2.24, SD = 0.94). Regarding conceptual understanding, 56.4% of students agreed that AI helped them understand financial concepts better (M = 2.51, SD = 0.84), though a notable 34.5% were indifferent. The reverse-coded item was rejected by 65.5% of respondents, with only 7.3% agreeing, suggesting that students perceived AI as additive rather than detrimental to their learning. Importantly, 69.1% reported that they checked the AI output before using it, indicating critical engagement with the technology.

Table 5
Student Perceptions of AI-Assisted Financial Literacy Instruction (n = 55)

AI Perception Item	*M*	*SD*	Agree %	Neutral %	Disagree %
AI helped understand financial concepts	2.51	0.84	56.4	34.5	9.1
AI improved group project efficiency	2.22	0.88	69.1	23.6	7.3
Learned to use AI effectively	2.09	0.82	81.8	10.9	7.3
Confident using AI for future work	2.24	0.94	70.9	14.5	14.5
Would have learned more without AI*	3.73	0.87	7.3	27.3	65.5
Checked AI output before using	2.24	0.96	69.1	16.4	14.5

Note. Scale: 1 = Strongly Agree to 5 = Strongly Disagree. Lower means indicate stronger agreement. *Reverse-coded item. Agree = Strongly Agree + Agree; Disagree = Disagree + Strongly Disagree.

Research Question 3: Financial Self-Efficacy

Research Question 3 asked to what extent students report financial self-efficacy in applying the financial planning concepts covered in the intervention. Four items measured students' perceived financial self-efficacy following the intervention (post-survey only; α = .678). As with the AI perception scale, this reliability coefficient is below the .70 threshold but is consistent with the exploratory nature of this instrument and the limited number of items. As Table 6 shows, the highest self-efficacy was reported for understanding the importance of an emergency fund, with 78.2% agreeing or strongly agreeing (M = 2.07, SD = 0.86). Over half of participants felt confident creating a simple monthly budget (56.4%; M = 2.60, SD = 1.12), and 63.6% indicated that they knew how to calculate retirement needs (M = 2.62, SD = 1.25). However, confidence was markedly lower for explaining the 4% rule and its relationship to retirement, with only 27.3% agreeing and 49.1% disagreeing (M = 3.25, SD = 1.13). This pattern suggests that while students gained confidence in general financial planning concepts, more specialized knowledge, such as the 4% rule, may require additional instructional scaffolding.

Table 6
Post-intervention Financial Self-Efficacy (n = 55)

Self-Efficacy Item	*M*	*SD*	Agree %	Neutral %	Disagree %
Confident creating monthly budget	2.60	1.12	56.4	16.4	27.3
Understand emergency fund importance	2.07	0.86	78.2	12.7	9.1
Know how to calculate retirement needs	2.62	1.25	63.6	7.3	29.1
Can explain the 4% rule	3.25	1.13	27.3	23.6	49.1

Note. Scale: 1 = Strongly Agree to 5 = Strongly Disagree. Lower means indicate stronger agreement.

Relationships Among Post-intervention Measures

Pearson correlations were computed to examine relationships among the post-survey measures. The composite AI perception score was not significantly correlated with either financial knowledge (r = .138, p = .316) or financial self-efficacy (r = .137, p = .318). These non-significant correlations suggest that students' positive perceptions of AI as a learning tool did not directly translate into higher knowledge scores or greater financial self-efficacy, and that the pathways through which AI-assisted instruction may influence financial literacy outcomes warrant further investigation.

Research Question 4: Qualitative Findings

Research Question 4 asked what themes emerge from students' essays, presentations, and AI interaction logs regarding their engagement with AI tools and application of financial planning concepts across the AIAS levels. The thematic analysis of 101 student artifacts and AI interaction logs revealed that the structured, progressive integration of AI allowed students to move beyond generic financial advice toward highly personalized, logically sound financial strategies.

Theme 1: Localized Optimization and Problem Solving

A recurring theme was the use of AI to solve localized financial constraints that students found difficult to navigate manually. By using AI as a collaborative tool at AIAS Levels 2–3, students identified specific solutions grounded in the Japanese context for their assigned personas.

Student 511-04 (Persona: Hiroshi) wrote: "I recommended him to move to a suburban area that is close to his work and receive company assistance. This change allowed him to reduce the expenses from ¥180,000 to ¥100,000." Student 522-09 (Persona: Yumi) reported: "I used AI to find specific discount grocery stores in her neighborhood. By switching to 'Gyomu Super,' we saved ¥15,000 monthly, which AI then calculated into her NISA investment plan."

Theme 2: Structural Reasoning and the Logic Architect

Students utilized the AI to bridge the gap between raw data and a cohesive financial narrative. The AI acted as what might be termed a logic architect, helping students structure their arguments around the 50/30/20 and 4% rules learned in Session 1.

Student 511-12 reflected: “To live a wonderful life of saving, it is important to review a current situation, make a financial plan, and make a retirement strategy. AI helped me see how these three things connect together.” Student 515-02 noted: “At first, I didn’t understand why the 4% rule mattered. But after the AI showed me 20 different years of market data, I realized that saving is about managing risk, not just having money.”

Theme 3: Anxiety Reduction Through Metacognitive Awareness

Perhaps the most significant qualitative shift was the reduction in financial anxiety. By simulating long-term outcomes, the AI provided a sense of agency that manual calculations alone could not provide.

Student 519-18 wrote: “I understand that this anxiety comes from a lack of knowledge. Therefore, I need to learn more about financial matters and build a more secure future, too. The AI plan showed me that even with a small salary, retirement is possible if I start now.” Student 511-21 stated: “I was scared of the stock market. But the AI simulation showed that even if the market crashes, the 4% rule protects me. I feel more confident to try investing now.”

Discussion

The present study examined whether a brief, three-session AI-assisted financial literacy intervention structured around the AIAS could influence Japanese university students' financial knowledge, saving behavior, and attitudes. The findings paint a nuanced picture: while quantitative measures showed no significant pre-post changes, the post-intervention survey and qualitative data revealed meaningful engagement with both AI and financial planning concepts.

Interpretation of Quantitative Findings

The absence of significant changes in financial knowledge, saving behavior, or attitudes is not entirely surprising given the intervention's brevity. Three 90-minute sessions likely provided insufficient time to shift deeply rooted financial behaviors or significantly increase factual knowledge. Moreover, relatively high pre-intervention knowledge scores (M = 3.92 out of 5) suggest a possible ceiling effect. The YFLSS measures recognition-level knowledge, which may not capture the applied financial reasoning that the intervention was designed to develop. These findings are consistent with Gorham and Mills (2025), who found that instructional design variables may matter more than AI access alone.

Regarding students' perceptions of AI-assisted learning, the post-intervention data indicate a largely favorable response. The finding that 81.8% felt they had learned to use AI effectively and 69.1% reported checking AI output before using it suggests the AIAS-structured progression helped develop both practical AI skills and a critical disposition toward AI-generated content. Introducing AI only after foundational knowledge was established may have contributed to this critical engagement.

As for financial self-efficacy, the pattern of strong confidence in budgeting and emergency funds but low confidence regarding the 4% rule suggests the intervention was more effective at building confidence in broadly applicable financial concepts than in specialized technical knowledge. This underscores the importance of distinguishing between general and specialized financial self-efficacy when evaluating short-term interventions.

Integration of Quantitative and Qualitative Results

The divergence between null quantitative results and rich qualitative findings is perhaps the most instructive aspect of this study. Thematic analysis revealed that students engaged in sophisticated financial reasoning, localized advice to the Japanese context, used AI to structure multi-step financial plans, and reported reduced financial anxiety. These outcomes suggest the intervention's value lay at a level that standardized instruments were not designed to capture, consistent with a view of AI as a cognitive scaffold for complex, real-world tasks.

Conclusion

The quantitative results showed no significant pre-post changes, indicating that three sessions were insufficient to shift standardized literacy scores. However, post-intervention data revealed favorable views of AI-assisted learning, moderate to strong self-efficacy in several financial planning domains, and qualitative evidence of substantive, critically reflective AI engagement.

These findings carry several implications. First, the value of short-term AI-assisted interventions may be less about improving test scores and more about building applied competence, reducing financial anxiety, and developing critical AI use, outcomes that matter in a Japanese context where financial confidence remains low despite growing policy attention (Financial Services Agency, 2023; Sticha & Lusardi, 2023). Second, the AIAS framework (Perkins et al., 2024) proved practical for structuring progressive AI integration, helping ensure critical rather than passive engagement. Third, the divergence between quantitative and qualitative findings highlights the importance of mixed-methods designs, as standardized instruments alone may underestimate the depth of student learning.

Several limitations should be acknowledged. The anonymous survey design prevented matched pre-post comparisons. The 44.4% attrition rate introduces possible non-response bias. The intervention was brief and embedded in EFL courses where financial literacy was not the primary focus. The sample was drawn from a single private university. The supplementary scales for AI perceptions (α = .625) and financial self-efficacy (α = .678) have not been independently validated. Finally, the qualitative analysis was conducted by a single researcher on a subset of student artifacts.

Future research should employ matched or longitudinal designs, extend the intervention period, and replicate across multiple institutions. Researchers might also develop performance-based assessments aligned with the applied learning revealed by qualitative data, and investigate specific mechanisms by which AI-assisted instruction influences financial self-efficacy, potentially through experimental designs comparing AIAS-structured integration with unstructured AI access.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

The author declares that generative AI tools were used during the research and writing process. During data analysis, Gemini and Claude were used for preliminary statistical calculations, which were subsequently verified using SPSS version 31. During the writing process, Claude was used for proofreading, language refinement, and formatting assistance. The ideas, research design, data collection, analysis, and interpretation are the original work of the authors.

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