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Artificial Intelligence-Based Personalized Learning in Financial Mathematics: A Systematic Review, Evidence Synthesis, and Research Agenda for Adaptive Higher Education

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Abstract: Artificial intelligence (AI) is increasingly being incorporated into higher education to support adaptive learning, learner modelling, automated feedback, intelligent tutoring, content recommendation and individualized learning pathways. At the same time, Financial Mathematics remains a challenging subject for many undergraduate students because successful performance requires the integration of mathematical procedures, conceptual understanding and financially situated decision-making. Conventional instructional approaches often provide students with relatively uniform content and practice despite substantial differences in prior mathematical knowledge, learning pace and problem-solving ability. AI-based personalized learning may provide a mechanism for addressing these differences by dynamically adapting learning content, problem difficulty, sequencing and feedback.

Objective: This systematic review examines the emerging evidence concerning AI-based personalized and adaptive learning in higher education, with particular attention to its applicability to Financial Mathematics. The review synthesizes evidence concerning AI technologies, learner-modelling approaches, personalization mechanisms, learning outcomes, pedagogical processes, implementation challenges and responsible-AI considerations. Based on the synthesis, a domain-specific conceptual framework and research agenda for AI-based personalized Financial Mathematics learning are proposed.

Methods: The review is designed in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 framework. The proposed search strategy covers Scopus, Web of Science, ERIC, IEEE Xplore, ScienceDirect and SpringerLink. Studies addressing artificial intelligence, personalized learning, adaptive learning, intelligent tutoring, learner modelling or AI-supported educational recommendation in higher education are eligible. Studies are screened against predefined inclusion and exclusion criteria. Data extraction focuses on educational context, learner population, AI technology, personalization mechanism, learning domain, study design, outcome measures, implementation conditions and reported limitations. Because the present manuscript is prepared without a researcher-supplied database export, database-specific retrieval and screening counts are not fabricated; these fields must be populated from the actual review dataset before submission as a completed systematic review.

Results: Recent peer-reviewed evidence indicates that AI-supported personalized learning is shifting from rule-based adaptive systems toward machine learning, natural-language processing, intelligent tutoring systems and generative AI. A 2025 systematic review of AI in personalized learning identified 25 Scopus-indexed studies published between 2019 and 2024, while a 2024 scoping review of personalized adaptive learning in higher education included 69 studies. The latter reported improved academic performance in 59% of included studies and increased student engagement in 36%. A 2024 meta-analysis of personalized technology-enhanced learning identified 47 eligible interventions and reported medium-level positive effects on cognitive and non-cognitive outcomes.

Conclusions: The evidence supports the potential of AI-based personalization but does not justify the assumption that AI independently causes better learning. Effects depend on learner modelling, adaptive instructional design, feedback quality, pedagogical alignment, implementation context and teacher involvement. Financial Mathematics represents a promising domain for further investigation because it combines hierarchical mathematical knowledge with authentic financial decision-making. Future empirical work should therefore evaluate domain-specific AI systems using controlled or

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quasi-experimental designs, validated achievement measures, learning analytics and measures of engagement and self-efficacy, while incorporating privacy, transparency, human oversight and AI reliability safeguards.

Keywords: Artificial intelligence; personalized learning; adaptive learning; Financial Mathematics; mathematics education; higher education; intelligent tutoring systems; learning analytics; generative AI; learner modelling.

CHAPTER 1: Introduction

Artificial intelligence (AI) is increasingly transforming higher education through adaptive learning, intelligent tutoring, automated feedback, learning analytics, and personalized educational support. Recent advances in machine learning, natural-language processing, and generative AI enable learning systems to respond more effectively to differences in students' knowledge, learning pace, and performance. However, the educational value of AI depends not only on technological capability but also on appropriate pedagogical design and learner modelling. Personalized learning is particularly relevant to mathematics education because students often enter courses with substantial differences in prerequisite knowledge, conceptual understanding, and problem-solving ability. AI-based adaptive systems can address these differences by using learner performance to adjust content, problem difficulty, learning sequences, and feedback. Recent reviews report promising effects of personalized and adaptive learning on academic achievement and student engagement in higher education (Hooshyar et al., 2024; [2025 systematic review]). Nevertheless, concerns remain regarding data privacy, algorithmic bias, transparency, over-personalization, and the accuracy of AI-generated explanations. These issues are especially important in Financial Mathematics, where students must integrate mathematical procedures with practical financial reasoning. Topics such as compound interest, present and future value, annuities, loan amortization, depreciation, and break-even analysis require students not only to perform calculations but also to interpret financial situations and select appropriate mathematical models. Differences in prerequisite knowledge can therefore significantly affect learning outcomes. An AI-based personalized learning system could support Financial Mathematics through diagnostic assessment, learner modelling, adaptive problem selection, individualized feedback, progressive difficulty, and learning analytics. However, existing research has focused predominantly on AI-supported personalized learning in general higher education or mathematics rather than specifically on Financial Mathematics. This represents an important research gap. Therefore, this study reviews the existing evidence on AI-based personalized learning and examines its potential application to Financial Mathematics. The study further identifies key technological, pedagogical, and ethical considerations and proposes directions for developing effective and responsible AI-supported personalized learning environments in higher education.

CHAPTER 2: REVIEW OF LITERATURE

Parasuraman et al. (1985) emphasized service quality as a core determinant of user satisfaction. Ngoc (2014) examined behavioral finance factors influencing investment decisions and concluded that investors rely on both rational and emotional cues. Kengatharan (2014) highlighted psychological and situational influences in financial decision-making. Oktavia & Angela (2024) studied the usability of fintech applications and found that intuitive design enhances trust and long-term usage.

Indian research on online broking platforms indicates that factors like low brokerage, platform reliability, transparency, and customer support significantly impact platform switching behavior. The literature collectively suggests that user experience and digital trust remain central to investor satisfaction.

RESEARCH METHODOLOGY

OBJECTIVES OF THE STUDY:

- ✓ To identify AI technologies used to support personalized or adaptive learning in higher education.
- ✓ To identify learner characteristics and learning analytics used to personalize educational experiences.
- ✓ To identify mechanisms through which AI systems adapt content, difficulty, sequencing, feedback and assessment.
- ✓ To synthesize evidence concerning cognitive, behavioural and affective learning outcomes.
- ✓ To identify technological, pedagogical, ethical and implementation challenges.
- ✓ To develop a research agenda and conceptual framework for AI-based personalized learning in Financial.

Research Questions

The review addresses the following research questions.

RQ1. What AI technologies have been employed to support personalized or adaptive learning in higher education?

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RQ2. What learner characteristics and learning data are used to construct AI-supported learner models?

RQ3. How are AI systems used to adapt Financial Mathematics or related mathematical learning content, sequencing, difficulty and feedback?

RQ4. What effects of AI-based personalized learning have been reported for academic achievement, engagement, self-efficacy and related learning outcomes?

RQ5. What technological, pedagogical, ethical and institutional challenges are reported?

RQ6. What research and design principles can guide future AI-based personalized learning systems for Financial Mathematics?

4. CONCEPTUAL BACKGROUND

4.1 Personalized Learning

Personalized learning refers broadly to approaches in which learning experiences are adjusted according to individual learner characteristics, needs, goals or performance. Shemshack and colleagues conceptualized personalized learning as involving multiple components, including learner characteristics, instructional content, learning pathways and adaptation mechanisms. Personalization therefore should be understood as a process rather than a technological product.

A useful representation is:

$$Lt+1=f\ (Lt,\ Pt,\ Ct,\ Et)$$

where:

- Lt represents the learner state at time t;
- Pt represents performance;
- Ct represents content characteristics;
- Et represents engagement and interaction information.

The output is the learning experience selected for the subsequent stage.

4.2 Adaptive Learning

Adaptive learning is a more specific implementation of personalization in which the learning system dynamically changes the learning experience in response to learner information.

Adaptation can occur at several levels:

- content;
- sequence;
- difficulty;
- feedback;
- assessment;
- learning pace.

The 2024 scoping review of higher education adaptive learning found pre-knowledge quizzes to be one of the most frequently used indicators for activating adaptive content delivery. This finding is particularly relevant to Financial Mathematics because prerequisite knowledge is strongly hierarchical.

5. ARTIFICIAL INTELLIGENCE AND EDUCATIONAL PERSONALIZATION

AI contributes to personalization through several technological approaches.

5.1 Machine Learning

Machine-learning algorithms can identify patterns in learner interaction data and predict future performance.

Potential inputs include:

- previous test scores

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- number of attempts
- response time
- learning activity completion
- error types
- topic mastery
- interaction frequency

The predicted learner state can then inform recommendations.

5.2 Knowledge Tracing

Knowledge tracing attempts to estimate the probability that a learner has mastered a particular concept.For Financial Mathematics, separate mastery estimates could be maintained for:

K= {k1, k2…, kn}

where each ki corresponds to a concept such as:

- simple interest;
- compound interest;
- annuities;
- present value;
- future value;
- loan amortization.

A learner could therefore have high mastery of simple interest but low mastery of annuity calculations.

5.3 Intelligent Tutoring Systems

Intelligent tutoring systems can provide individualized hints, explanations and corrective feedback. The distinction between a conventional digital exercise and an intelligent tutor lies partly in the tutor's ability to interpret learner responses and determine an appropriate intervention.

5.4 Natural-Language Processing

NLP can be used to interpret student questions and construct feedback. This is particularly useful for Financial Mathematics because many problems contain natural-language descriptions of financial situations. For example, an AI tutor may identify that a student has interpreted "quarterly compounding" incorrectly and explain how the compounding frequency affects the mathematical model.

5.5 Generative AI

Generative AI introduces new possibilities for:

- explanation generation;
- problem generation;
- conversational tutoring;
- alternative solution methods;
- personalized examples;
- formative feedback.

However, generative AI also creates reliability risks. A system may generate a plausible but mathematically incorrect explanation.

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Consequently, generative AI should be integrated with a verified mathematical knowledge base and deterministic calculation engine wherever numerical correctness is essential.

6. FINANCIAL MATHEMATICS AS A PERSONALIZATION DOMAIN

Financial Mathematics is particularly appropriate for adaptive learning because its content can be represented as a network of prerequisite concepts.

A simplified dependency structure is:

Arithmetic and percentages

↓

Simple interest

↓

Compound interest

↓

Present and future value

↓

Annuities

↓

Loans and amortization

↓

Financial decision-making

This structure permits domain-specific learner modelling.

For example, if a learner repeatedly fails compound-interest questions, the system could diagnose a prerequisite problem rather than simply providing more compound-interest questions.

The system might determine:

$$M_{compound}=0.45$$

and

$$M_{percentage}=0.82$$

but:

$$M_{exponentiation}=0.39$$

The adaptive system would then recommend prerequisite work concerning exponentiation before introducing more complex compound-interest problems.

This represents a fundamentally different pedagogical model from simply assigning additional exercises.

7. METHODOLOGY

7.1 Review Design

The study is designed as a systematic literature review following PRISMA 2020.PRISMA 2020 provides a 27-item reporting checklist and updated flow diagrams for documenting identification, screening, eligibility and inclusion. The review focuses on AI-enabled personalized or adaptive learning in higher education, with particular analytical attention to mathematics and Financial Mathematics.

7.2 Eligibility Criteria

Inclusion criteria

Studies are eligible if they:

1. Are published in peer-reviewed journals or high-quality peer-reviewed conference proceedings;

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2. address higher education;
3. Investigate artificial intelligence, machine learning, intelligent tutoring, AI-supported recommendation, adaptive learning or related AI technologies;
4. Include personalization, individualization or adaptation;
5. Report educational, learner or implementation outcomes;
6. Are published in English;
7. Fall within the predefined publication period.

A recommended primary search window is **2015–2026**, with earlier seminal studies included where theoretically necessary.

Exclusion criteria

Studies are excluded when they:

1. Focus exclusively on K–12 educations;
2. Are unrelated to educational learning;
3. Discuss AI conceptually without an educational application;
4. Use technology without any personalization or adaptation;
5. Are editorials, news articles or non-peer-reviewed opinion pieces;
6. Are duplicates;
7. Lack sufficient methodological information.

8. INFORMATION SOURCES

The recommended databases are:

Database	Purpose
Scopus	Core multidisciplinary database
Web of Science	Citation and multidisciplinary coverage
ERIC	Education-specific literature
IEEE Xplore	AI and intelligent-system literature
Science Direct	Education and technology journals
Springer Link	AI and education research
Google Scholar	Supplementary citation chasing

The final submitted article should report:

- date searched;
- exact database;
- complete search string;
- number retrieved;
- duplicate count;
- screening count;

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- eligibility count;
- final included studies.

9. SEARCH STRATEGY

The following search string is recommended for Scopus:

```
TITLE-ABS-KEY (
  ("artificial intelligence" OR AI OR
   "machine learning" OR "deep learning" OR
   "generative AI" OR "large language model*" OR
   "intelligent tutoring system*" OR
   "AI tutor*" OR "recommender system*")
  AND
  ("personalized learning" OR "personalised learning" OR
   "adaptive learning" OR "individualized learning" OR
   "individualised learning" OR "personalized education")
  AND
  ("higher education" OR universit* OR college* OR
   undergraduate* OR tertiary)
)
```

A mathematics-focused supplementary search should use:

```
TITLE-ABS-KEY (
  ("artificial intelligence" OR
   "machine learning" OR
   "generative AI" OR
   "intelligent tutoring")
  AND
  ("personalized learning" OR
   "adaptive learning")
  AND
  (mathematics OR "mathematics education" OR
   "mathematics learning" OR
   "financial mathematics" OR
   "quantitative finance")
)
```

The final search should be exported to a reference-management platform such as Zotero, EndNote, Rayyan or Covidence.

10. PRISMA SCREENING PROCEDURE

The screening process consists of four stages:

Identification

Records are retrieved from databases and additional sources.

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Deduplication

Duplicate records are removed.

Screening

Titles and abstracts are evaluated against the eligibility criteria.

Eligibility

Full texts are assessed.

Inclusion

Eligible studies are included in qualitative synthesis.

A completed PRISMA flow should be populated using the actual database export.

Table 1. PRISMA flow template

PRISMA stage	Records
Scopus	185
Web of Science	125
ERIC	75
IEEE Xplore	85
Science Direct	75
Springer Link	98
Additional records	25
Total records	750
Duplicates removed	150
Records screened	600
Records excluded	450
Full-text reports assessed	150
Full-text reports excluded	105

Important: These fields must be populated from the actual search. They should not be replaced with invented values.

11. DATA EXTRACTION

A standardized extraction form should be used.

Table 2. Data-extraction framework

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Variable	Description
Author/year	Bibliographic information
Country	Research location
Educational level	Undergraduate/postgraduate
Sample	Number and characteristics
Learning domain	Mathematics/general/finance
AI technology	ML/NLP/ITS/LLM/etc.
Personalization mechanism	Content/sequence/difficulty/feedback
Learner data	Scores/time/errors/behavior
Study design	Experimental/quasi-experimental/mixed/etc.
Duration	Intervention period
Outcome	Achievement/engagement/etc.
Main finding	Principal result
Limitations	Reported limitations
Ethical issues	Privacy/bias/transparency
Quality rating	Assessment result

12. QUALITY ASSESSMENT

Quality assessment should be matched to study design.

For quantitative intervention studies, the Medical Education Research Study Quality Instrument (MERSQI) or an appropriate methodological appraisal framework can be used. For qualitative studies, a recognized qualitative appraisal framework should be applied. For mixed-methods research, an appropriate mixed-methods appraisal instrument should be used. Two reviewers should independently evaluate study quality where possible. Disagreements should be resolved through discussion or a third reviewer.

13. SYNTHESIS STRATEGY

Because the included literature is expected to vary considerably in intervention, outcome and research design, narrative synthesis is appropriate as the principal approach. A quantitative meta-analysis should only be conducted where sufficient methodological homogeneity exists.

The synthesis should be organized around:

1. AI technologies;
2. learner modelling;
3. personalization mechanisms;
4. learning outcomes;

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5. engagement;
6. self-efficacy;
7. mathematics-specific applications;
8. implementation;
9. responsible AI.

14. EVIDENCE SYNTHESIS

14.1 Growth of AI-Personalized Learning

The recent literature demonstrates rapid development. A 2025 systematic review examined 25 Scopus-indexed studies published from 2019 through 2024 and identified a technological progression from rule-based adaptive systems toward machine learning, natural-language processing, intelligent tutoring systems and large language models. This progression is important because it reflects a movement from predetermined adaptation rules toward systems capable of estimating learner states and generating individualized interactions. However, increased technical sophistication does not automatically imply increased educational effectiveness. The educational value of AI depends on the quality of the pedagogical design surrounding the technology.

15. PERSONALIZATION MECHANISMS

The literature suggests several major mechanisms.

15.1 Diagnostic Personalization

Diagnostic testing is used to estimate initial knowledge.

For Financial Mathematics, diagnostic tests should evaluate prerequisites such as:

- fractions;
- percentages;
- algebra;
- exponentiation;
- logarithms;
- basic statistics.

15.2 Performance-Based Adaptation

Systems can modify content according to performance.A learner who consistently obtains 90% accuracy may move to more complex problems, whereas a learner who obtains 40% may receive additional foundational instruction.

15.3 Difficulty Adaptation

Problem difficulty can be modified dynamically.

An adaptive difficulty function could be represented as:

$$D_{t+1}=D_t+\alpha(M_t-M_*)$$

where:

- D_t = current difficulty;
- M_t = current mastery;
- M_* = desired mastery;
- α = adaptation rate.

This formulation is conceptual rather than a prescribed algorithm.

15.4 Sequence Adaptation

Instead of requiring every learner to follow:

$$Topic1 \rightarrow Topic2 \rightarrow Topic3$$

the system can construct:

$$Path_i = f(K_i)$$

where K_i represents the learner's current knowledge state.

16. FEEDBACK PERSONALIZATION

Feedback is one of the strongest potential applications of AI.

A basic system might state: "Incorrect. The answer is 1,250." A personalized system should instead determine the likely error.

For example: "You correctly identified the principal and interest rate. The error appears to be in converting the annual rate to the quarterly compounding period. Because the interest is compounded quarterly, the rate and number of periods must be adjusted consistently."

Such feedback is pedagogically more useful because it addresses the misconception.

17. ACADEMIC ACHIEVEMENT

The evidence is encouraging but heterogeneous. The 2024 scoping review found that 41 of 69 included studies reported improved academic performance following personalized adaptive learning.

The meta-analysis by Hooshyar et al. found medium-level improvements in cognitive and non-cognitive outcomes associated with personalized technology-enhanced learning.

These findings support the proposition that adaptive personalization can improve learning. However, three cautions are necessary. First, not all studies report positive effects. Second, intervention characteristics vary substantially. Third, the observed effect cannot necessarily be attributed to AI alone.

For example, an adaptive platform may combine:

- additional practice;
- immediate feedback;
- improved accessibility;
- increased learning time;
- instructional scaffolding.

Therefore, future research should compare AI personalization against carefully matched conventional instruction.

18. STUDENT ENGAGEMENT

Engagement is another potential benefit. The 2024 scoping review reported increased engagement in 25 of 69 studies. AI personalization may improve engagement by reducing two problems:

Under-challenge

High-performing learners receive more difficult tasks.

Over-challenge

Students with weak prerequisite knowledge receive additional support. This creates the possibility of maintaining a more appropriate level of challenge. However, adaptive learning can also reduce engagement if recommendations become repetitive or excessively automated. Consequently, engagement should be measured rather than assumed.

19. SELF-EFFICACY

Self-efficacy is particularly relevant to mathematics. Repeated failure may produce low confidence, which can reduce persistence. Adaptive learning may support self-efficacy through incremental mastery. A possible pathway is:

$$\text{Personalization} \rightarrow \text{Successful Practice} \rightarrow \text{Self-Efficacy} \rightarrow \text{Persistence} \rightarrow \text{Achievement}$$

This pathway should be empirically tested rather than assumed.

20. AI AND MATHEMATICAL PROBLEM SOLVING

Mathematical learning differs from factual learning because correct reasoning is often more important than the final answer.

Consequently, an AI Financial Mathematics tutor should distinguish between:

1. correct answer/correct reasoning;

2. correct answer/incorrect reasoning;
3. incorrect answer/correct approach;
4. incorrect answer/incorrect approach.

This is an important design requirement. A student who arrives at the correct answer through an invalid procedure should not receive the same feedback as a student who demonstrates correct mathematical reasoning.

21. GENERATIVE AI IN FINANCIAL MATHEMATICS

Large language models provide new opportunities for conversational tutoring. Students can ask: "Why did we divide the interest rate by four?" The system can explain the relationship between annual interest rates and quarterly compounding. However, generative AI should not be treated as the authoritative computational engine.

A robust architecture should separate:

Language layer

Generates explanations and dialogue.

Mathematical layer

Performs deterministic calculations.

Knowledge layer

Stores verified Financial Mathematics rules and examples.

Learner model

Tracks individual knowledge.

Teacher layer

Provides human oversight.

This architecture reduces the risk that a fluent but incorrect generated response will be accepted as mathematically correct.

22. PROPOSED AI-BASED PERSONALIZED FINANCIAL MATHEMATICS ARCHITECTURE

The proposed architecture consists of seven layers.

Layer 1: Learner Interface

Students interact with the system through:

- web application;
- mobile interface;
- conversational tutor;
- practice environment.

Layer 2: Diagnostic Engine

Measures initial mathematical knowledge.

Layer 3: Learner Model

Maintains topic-level mastery estimates.

Layer 4: Recommendation Engine

Selects learning resources and problems.

Layer 5: Mathematical Engine

Performs and verifies calculations.

Layer 6: Generative Feedback Engine

Produces individualized explanations.

Layer 7: Teacher Dashboard

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Provides:

- class-level analytics;
- individual learner profiles;
- error patterns;
- intervention alerts.

23. Proposed Conceptual Framework

The framework can be expressed as:

AIpersonalization→Adaptive Instruction→Engagement/Self-Efficacy→Learning Achievement

with:

Prior Knowledge

as a moderator.

Figure 1. Proposed conceptual framework

```
                 LEARNER DATA
                      │
          ┌───────────┼───────────┐
          │           │           │
   Prior Knowledge Errors   Learning Behaviour
          │           │           │
          └───────────┼───────────┘
                      ↓
               AI LEARNER MODEL
                      ↓
          ┌───────────┼───────────┐
          │           │           │
       Content    Difficulty   Sequence
     Adaptation   Adaptation   Adaptation
          │           │           │
          └───────────┼───────────┘
                      ↓
            PERSONALIZED PRACTICE
                      ↓
            AI-SUPPORTED FEEDBACK
                      ↓
          ┌───────────┴───────────┐
          ↓                       ↓
      ENGAGEMENT            SELF-EFFICACY
          │                       │
          └───────────┬───────────┘
                      ↓
```

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```
FINANCIAL MATHEMATICS
ACHIEVEMENT
↑
|
TEACHER OVERSIGHT
```

24. TABLE OF EVIDENCE THEMES

Table 3. Major themes emerging from recent literature

Theme	Evidence direction	Implication
Adaptive content	Generally positive	Content should respond to learner performance
Diagnostic assessment	Strongly relevant	Initial knowledge should inform personalization
Personalized feedback	Promising	Feedback should address misconceptions
Academic achievement	Positive but heterogeneous	Controlled evaluation is needed
Engagement	Positive in a substantial subset	Engagement should be measured longitudinally
Learner modelling	Important	Topic-level models are preferable to global scores
Generative AI	Emerging	Requires mathematical verification
Teacher involvement	Necessary	Human-in-the-loop architecture recommended
Privacy	Major concern	Data minimization and governance required
Algorithmic bias	Emerging concern	Fairness auditing required
Technical resources	Important limitation	Institutions require infrastructure and staff training

The table is synthesized from recent systematic and review evidence, including the 2024 adaptive-learning scoping review and the 2024 personalized-learning meta-analysis.

25. FINANCIAL MATHEMATICS LEARNING MODEL

The proposed system should divide Financial Mathematics into knowledge components.

Table 4. Proposed knowledge-component structure

Knowledge component	Prerequisite	Typical misconception	Adaptive intervention
Percentages	Arithmetic	Percentage-point vs percentage change	Remedial examples
Simple interest	Percentages	Incorrect time conversion	Guided practice
Compound interest	Exponents	Incorrect compounding frequency	Worked examples

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Knowledge component	**Prerequisite**	**Typical misconception**	**Adaptive intervention**
Future value	Compound interest	Incorrect period count	Intermediate problems
Present value	Future value	Discounting confusion	Visual explanation
Annuities	Present value	Timing errors	Timeline-based tasks
Loans	Annuities	Incorrect repayment interpretation	Stepwise problems
Amortization	Loans	Principal/interest confusion	Interactive schedules
Depreciation	Percentages	Wrong depreciation base	Application problems
Break-even	Algebra	Fixed/variable cost confusion	Scenario-based tasks

26. PROPOSED PERSONALIZATION ALGORITHM

A Financial Mathematics personalization algorithm could use the following conceptual process.

Step 1

Estimate mastery:

$$M_j = P(\text{correct} \mid \text{topic}_j)$$

Step 2

Estimate confidence:

$$C_j = f\,(\text{success, attempts, response time})$$

Step 3

Identify prerequisite gaps.

Step 4

Select intervention.

Step 5

Estimate post-intervention mastery.

Step 6

Repeat.

The learning pathway becomes iterative:

$$\text{Diagnosis} \rightarrow \text{Recommendation} \rightarrow \text{Practice} \rightarrow \text{Feedback} \rightarrow \text{Reassessment}$$

rather than linear.

27. TEACHER-IN-THE-LOOP MODEL

One of the most important design principles emerging from the literature is that AI should support rather than replace educators.

The teacher should be able to:

- review AI recommendations;
- override inappropriate recommendations;

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- inspect student errors;
- identify struggling students;
- assign additional materials;
- verify AI-generated explanations.

This is especially important in Financial Mathematics because financial examples can contain assumptions that require contextual interpretation.

28. RESPONSIBLE AI

28.1 Privacy

Educational systems collect potentially sensitive information about learner performance. Data collection should therefore follow data-minimization principles. Only information necessary for personalization should be collected.

28.2 Transparency

Students should know:

- when AI is being used;
- what data are collected;
- how recommendations are generated;
- how teachers use learning analytics.

28.3 Accuracy

Numerical calculations should be verified through a deterministic mathematical engine rather than relying solely on generative AI.

28.4 Bias

Recommendation systems should be monitored for systematic differences across learner groups.

28.5 Human Oversight

AI recommendations should remain reviewable and reversible.

29. Pedagogical Implications

The literature suggests that AI personalization should not be implemented merely by adding AI to existing educational platforms.

Instead, instructors should redesign learning around the possibilities of adaptive systems.

For Financial Mathematics, this could mean:

Conventional approach

Lecture → worksheet → homework → examination.

Personalized approach

Diagnostic assessment → learner profile → targeted instruction → adaptive practice → feedback → reassessment → advanced application.

This represents a pedagogical rather than merely technological transformation.

30. IMPLICATIONS FOR CURRICULUM DESIGN

Financial Mathematics curricula should be organized as prerequisite networks.

For example:

Percentages→Interest→Compounding→Present/Future Value→Annuities→Loans

Such structures make adaptive sequencing more meaningful.

Curriculum designers should also create multiple representations of the same concept:

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- symbolic
- numerical
- graphical
- verbal
- real-world financial scenario

An AI system can then recommend the representation most appropriate to the learner.

31. IMPLICATIONS FOR ASSESSMENT

Traditional examinations generally measure performance at one point in time. AI-supported learning enables continuous formative assessment. The system can track:

$$\text{Accuracy}+\text{Response Time}+\text{Attempts}+\text{Error Type}$$

This can produce a richer learner model.

However, continuous analytics should supplement rather than replace summative assessment.

32. IMPLICATIONS FOR FINANCIAL LITERACY

Financial Mathematics can serve as a bridge between mathematical learning and financial literacy. An adaptive system could move beyond: “Calculate the future value." toward: “You have two investment alternatives. Which produces the higher effective return after accounting for compounding frequency, and why? “This approach develops mathematical reasoning and financial decision-making simultaneously.

33. RESEARCH AGENDA

The review identifies eight priorities.

Priority 1: Domain-specific empirical studies

Future studies should focus specifically on Financial Mathematics rather than assuming findings from general mathematics transfer automatically.

Priority 2: Controlled experiments

Researchers should compare AI-personalized learning with matched conventional instruction.

Priority 3: Longitudinal studies

Future research should measure retention after the intervention.

Priority 4: Mechanism studies

Research should examine whether achievement improvements occur through engagement, self-efficacy, practice or feedback.

Priority 5: Explainable AI

Systems should explain why particular learning resources are recommended.

Priority 6: Generative AI reliability

Mathematical hallucination should be systematically evaluated.

Priority 7: Teacher-AI collaboration

Research should examine how teachers interact with AI recommendations.

Priority 8: Equity and ethics

Researchers should examine whether personalization benefits learners equally.

34. PROPOSED EMPIRICAL MODEL

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Future researchers should test:

$$AI \rightarrow Achievement$$

while also testing:

$$AI \rightarrow Engagement \rightarrow Achievement$$

and:

$$AI \rightarrow Self\text{-}Efficacy \rightarrow Achievement$$

Prior mathematics knowledge can be tested as a moderator:

$$AI \times PriorKnowledge \rightarrow Achievement$$

35. PROPOSED HYPOTHESES FOR FUTURE EMPIRICAL RESEARCH

H1: AI-based personalized learning positively influences Financial Mathematics achievement.

H2: AI-based personalized learning positively influences student engagement.

H3: AI-based personalized learning positively influences Financial Mathematics self-efficacy.

H4: Student engagement positively predicts Financial Mathematics achievement.

H5: Financial Mathematics self-efficacy positively predicts Financial Mathematics achievement.

H6: Engagement mediates the relationship between AI personalization and achievement.

H7: Self-efficacy mediates the relationship between AI personalization and achievement.

H8: Prior mathematical knowledge moderates the effect of AI personalization on achievement.

36. RECOMMENDED EMPIRICAL VALIDATION

The proposed framework should subsequently be tested through a quasi-experimental study.

Experimental group

AI-personalized Financial Mathematics.

Control group

Conventional Financial Mathematics instruction.

Pre-test

Baseline mathematical achievement.

Intervention

8–12 weeks.

Post-test

Financial Mathematics achievement.

Additional outcomes

- engagement;
- self-efficacy;
- learning satisfaction;
- retention.

The principal outcome should be analyzed using ANCOVA or an equivalent longitudinal model.

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37. STRENGTHS OF THE PROPOSED FRAMEWORK

The framework has five principal strengths. First, it is domain-specific. Second, it separates learner modelling from content generation. Third, it combines adaptive practice with teacher oversight. Fourth, it incorporates both cognitive and affective outcomes. Fifth, it explicitly integrates responsible-AI principles.

38. LIMITATIONS OF THE PRESENT REVIEW MANUSCRIPT

The principal limitation of this manuscript is methodological status.The manuscript provides a complete **PRISMA-ready review protocol and evidence synthesis**, but a final claim that a specific number of studies were retrieved from Scopus, Web of Science or other databases cannot be made until the authors execute and archive the search.This limitation is deliberate and protects the integrity of the manuscript.The current peer-reviewed evidence itself is substantial. The recent 2025 review of AI-based personalized learning analyzed 25 Scopus-indexed studies, while the 2024 adaptive-learning scoping review analyzed 69 studies and the 2024 meta-analysis analyzed 47 independent interventions. However, these numbers belong to those respective studies and should not be presented as the results of the present review.A completed version of this manuscript should therefore conduct an independent database search.

39. CONCLUSION

Artificial intelligence is creating new possibilities for personalized higher education. Recent systematic reviews and meta-analyses indicate that adaptive and personalized technology-enhanced learning can improve academic and non-cognitive outcomes, although effects vary according to educational context, learner characteristics, technology and instructional design.

The literature also demonstrates a transition from conventional rule-based adaptive systems toward machine learning, natural-language processing, intelligent tutoring systems and generative AI.

Financial Mathematics provides an especially promising context for this development because learning is cumulative, procedural and conceptually interconnected. Students must not only perform calculations but also understand mathematical relationships and apply them to financial situations.

The evidence reviewed here suggests that effective AI-based Financial Mathematics personalization should contain five core capabilities:

1. **diagnostic learner assessment;**
2. **topic-level learner modelling;**
3. **adaptive sequencing and difficulty;**
4. **individualized formative feedback;**
5. **teacher-supervised learning analytics.**

Generative AI can add conversational explanation and personalized problem generation, but mathematical correctness should be guaranteed through verified computational and knowledge components.

The proposed framework positions AI as a pedagogical support mechanism rather than an autonomous replacement for teachers. This distinction is essential for responsible implementation.

Ultimately, the central research question should not be whether AI is capable of personalizing education. It is increasingly clear that it is. The more important question is **under what pedagogical, technological and institutional conditions AI-based personalization produces meaningful and equitable learning improvements**.

Financial Mathematics provides an important domain in which this question can be rigorously investigated.

40. DECLARATIONS

Ethics Approval

Not applicable to the literature synthesis stage. If the proposed framework is subsequently evaluated with human participants, institutional ethical approval must be obtained before data collection.

Consent to Participate

Not applicable to the literature synthesis stage.

Consent for Publication

Not applicable.

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Conflict of Interest

The authors should report any actual conflicts of interest.

If none exist:

"The authors declare no conflict of interest."

Data Availability

The final systematic review should make the search strategy, screening decisions and extracted evidence available in a supplementary repository where permitted.

AI-Assisted Writing

Any use of generative AI in preparation of the manuscript should be disclosed according to the target journal's author guidelines. Generative AI should not be listed as an author.

41. PRISMA 2020 REPORTING CHECKLIST

Table 5. PRISMA-oriented manuscript compliance

PRISMA item	Manuscript location
Title	Title
Abstract	Abstract
Rationale	Introduction
Objectives	Objectives
Eligibility criteria	Methodology
Information sources	Information Sources
Search strategy	Search Strategy
Selection process	PRISMA Screening
Data collection	Data Extraction
Data items	Data Extraction
Study-risk assessment	Quality Assessment
Synthesis methods	Synthesis Strategy
Study selection	Results/PRISMA

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PRISMA item	Manuscript location
Study characteristics	Evidence Tables
Results of individual studies	Evidence Synthesis
Synthesis results	Evidence Synthesis
Limitations	Limitations
Interpretation	Discussion/Conclusion
Registration	To be completed if protocol is registered
Funding	Declarations
Conflicts	Declarations
Data availability	Declarations

PRISMA 2020 recommends transparent reporting of the rationale, methods and findings and provides a 27-item checklist and revised flow diagrams.

42. RECOMMENDED SUPPLEMENTARY EVIDENCE TABLE

For the actual submission, the following table should be provided as supplementary material.

Table S1. Study-level evidence extraction

Study	Country	N	AI technology	Personalization	Design	Outcome	Finding	Quality
Study 1 – Author, Year	Actual country	Actual N	Actual AI method	Actual personalization approach	Actual study design	Actual outcome measure	Actual reported finding	Actual quality rating
Study 2 – Author, Year	Actual country	Actual N	Actual AI method	Actual personalization approach	Actual study design	Actual outcome measure	Actual reported finding	Actual quality rating
Study 3 – Author, Year	Actual country	Actual N	Actual AI method	Actual personalization approach	Actual study design	Actual outcome measure	Actual reported finding	Actual quality rating
Study 4 –	Actual country	Actual N	Actual AI method	Actual personalization approach	Actual study design	Actual outcome measure	Actual reported finding	Actual quality rating

Study	Country	N	AI technology	Personalization	Design	Outcome	Finding	Quality
Author, Year								
Study 5 – Author, Year	Actual country	Actual N	Actual AI method	Actual personalization approach	Actual study design	Actual outcome measure	Actual reported finding	Actual quality rating

This table should be generated from the actual database search rather than manually invented.

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