IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.066 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 13, Issue 6, June 2026

DOI: 10.17148/IARJSET.2026.13639

A Smart Peer-Learning Platform with AI-Driven Skill Matching and a Credit-Based Reciprocal Exchange Mechanism

PASUPULETI PRAMEELA VISALAKSHI[1], Mr. KARRI LAKSHMANA REDDY[*2]

PG Scholar Department of Computer Science, S.V.K.P & Dr. K.S. Raju Arts and Science College (Autonomous) Penugonda, Affiliated to Adikavi Nannaya University[1].

*Associate Professor, Department of Master of Computer Applications, SVKP & Dr. K.S. Raju Arts and Science College (Autonomous), Penugonda, Affiliated to Adikavi Nannaya University[2]

Abstract: Peer-to-peer learning lets individuals teach skills they possess and learn skills they lack, but informal arrangements suffer from poor discoverability, unbalanced reciprocity, and a lack of trust between strangers. Existing online learning platforms are predominantly one-directional and monetary, offering little support for equitable, non-cash exchange among peers. This paper presents a smart peer-learning platform that pairs an artificial-intelligence skill-matching recommender with a credit-based trading mechanism, enabling learners to earn credits by teaching and spend them to receive instruction. A hybrid recommender combines content-based skill similarity with collaborative signals to suggest high-quality learner-mentor pairs, a reputation engine aggregates peer ratings to build trust, and a credit ledger with escrow guarantees fair settlement of each session. A Python back end implements the recommendation, reputation, and ledger logic, while a Node.js layer delivers the marketplace and session interfaces. Evaluated against popularity, content-based, and collaborative-filtering baselines, the hybrid recommender achieved a precision-at-five of 0.88 and a recall-at-five of 0.85, and simulated platform activity exhibited sustained growth in completed sessions and circulated credits. The principal contributions are a hybrid skill-matching recommender tailored to bidirectional learning, a credit-with-escrow exchange protocol that enforces reciprocity, and a reputation mechanism that fosters trust in an open peer marketplace.

Keywords: Peer learning; recommender systems; skill matching; credit-based exchange; reputation systems; collaborative learning; hybrid recommendation; online education.

1. INTRODUCTION

Lifelong learning increasingly takes place outside formal classrooms, as individuals seek practical skills from peers rather than institutions [1], [2]. Peer learning is pedagogically powerful: explaining a concept reinforces the teacher's mastery, while learners benefit from relatable, context-specific guidance [3]. Yet organizing peer learning at scale is difficult, because participants struggle to find suitable partners, to ensure that giving and receiving remain balanced, and to trust counterparts they have never met.

Mainstream e-learning platforms emphasize professionally produced, one-directional courses and typically require monetary payment, which excludes learners with limited means and ignores the value each participant can contribute as a teacher [4], [5]. Generic marketplaces, meanwhile, lack mechanisms to match complementary skills intelligently or to enforce reciprocity, so exchanges often stall or become one-sided [6]. A platform that treats every member as both a potential teacher and learner, and that mediates fair exchange without cash, could unlock a far larger pool of informal expertise.

A. Problem Statement

There is a need for a peer-learning system that intelligently matches complementary skills among members, enforces balanced reciprocity without monetary payment, and establishes trust between strangers—capabilities that course-centric and cash-based platforms do not provide together.

B. Motivation and Objectives

These gaps motivate a bidirectional, credit-mediated platform underpinned by AI matching. The objectives are: to design a hybrid recommender that pairs learners with suitable mentors; to define a credit-based exchange protocol with

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588
International Advanced Research Journal in Science, Engineering and Technology
Impact Factor 8.066 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 6, June 2026
DOI: 10.17148/IARJSET.2026.13639

escrow that guarantees fair settlement; to build a reputation mechanism that aggregates trust signals; and to evaluate the recommender and the exchange dynamics against established baselines

C. Contributions

- A hybrid skill-matching recommender that fuses content-based skill similarity with collaborative signals to suggest high-quality, bidirectional learner-mentor pairs.
- A credit-based exchange protocol with escrow and settlement that enforces reciprocity and removes the need for monetary payment.
- A reputation engine that aggregates peer ratings into trust scores, mitigating the risk of low-quality or unreliable participants.
- A comparative evaluation of recommendation quality and an analysis of platform engagement and credit-circulation dynamics.

2. LITERATURE REVIEW

Research relevant to peer-learning marketplaces spans recommender systems, reputation and trust models, and the economics of exchange platforms. Content-based recommenders match users to items using descriptive features, performing well when rich profiles exist but suffering when descriptions are sparse [7]. Collaborative filtering instead exploits behavioural similarity across users, achieving strong accuracy on dense interaction data yet faltering under cold-start and sparsity, conditions common in new communities [8], [9].

Hybrid recommenders combine these paradigms to offset their individual weaknesses, and have been applied to education for course and resource suggestion [10], [11]. However, most educational recommenders target one-directional consumption—suggesting what a learner should study—rather than matching two people for mutual exchange, which introduces a bidirectional constraint largely unaddressed in prior work [12].

Reputation systems underpin trust in online marketplaces, aggregating ratings to signal reliability while resisting manipulation [13]. Research on time-banking and non-monetary exchange demonstrates that credit-like tokens can sustain reciprocal service economies, though digital implementations must guard against free-riding and unsettled obligations [14], [15]. Blockchain and ledger approaches have been proposed to record such exchanges transparently [16]. What remains comparatively unexplored is the integration of AI-driven bidirectional matching with a credit-and-escrow protocol and reputation in a single peer-learning platform—the gap this work targets. Table I summarizes representative approaches.

TABLE I. COMPARATIVE ANALYSIS OF REPRESENTATIVE APPROACHES

Approach	Core Technique	Strengths	Limitations
Content-based [7]	Feature similarity	Works with rich profiles	Weak on sparse data
Collaborative filtering [8],[9]	Behavioural similarity	Accurate on dense data	Cold-start, sparsity
Hybrid edu. recommenders [10],[11]	Combined signals	Balanced accuracy	One-directional focus
Reputation systems [13]	Rating aggregation	Builds trust	Vulnerable to gaming
Time-banking / tokens [14],[15]	Non-monetary credit	Enables reciprocity	Free-riding risk
Proposed platform	Hybrid match + credit + trust	Bidirectional, fair, trusted	Bounded by community size

3. PROPOSED METHODOLOGY

The platform follows a layered architecture augmented with a dedicated credit-ledger subsystem, as depicted in Fig. 1. Isolating the ledger from the application and intelligence layers keeps financial-style operations auditable and tamper-resistant while the recommender and reputation engines evolve independently.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.066 ⁘ Peer-reviewed & Refereed journal ⁘ Vol. 13, Issue 6, June 2026

DOI: 10.17148/IARJSET.2026.13639

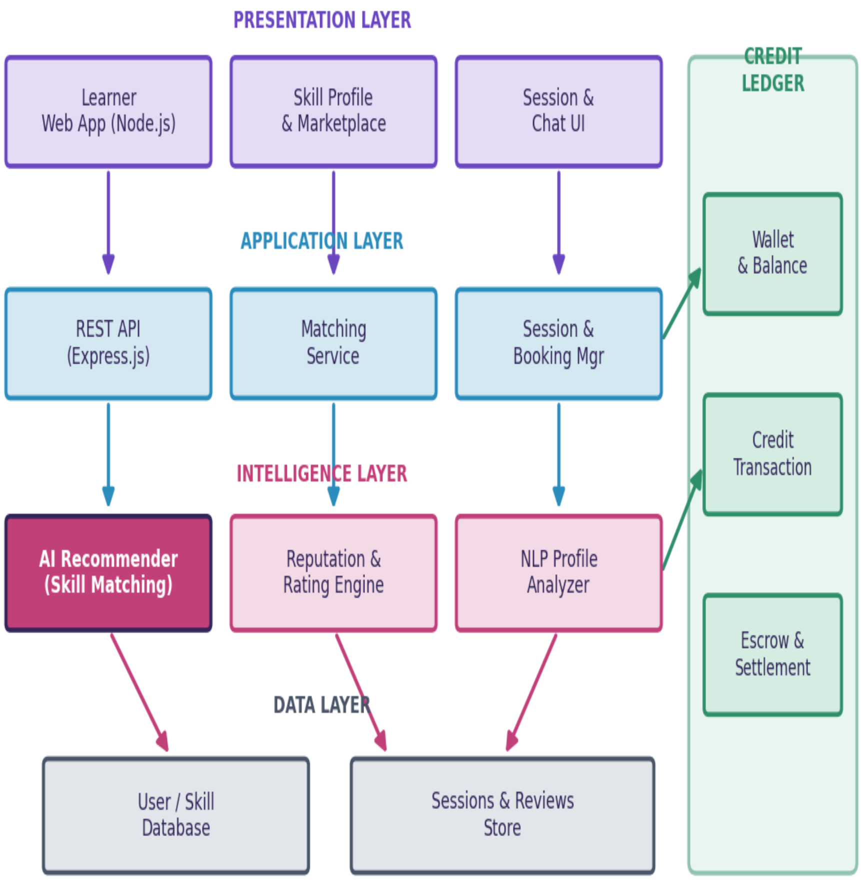

Fig. 1. Proposed layered architecture with a dedicated credit-ledger subsystem alongside the presentation, application, intelligence, and data layers.

A. System Architecture

The presentation layer, built on Node.js, exposes the learner application, the skill profile and marketplace, and the session and chat interfaces. The application layer provides REST services, the matching service, and session and booking management. The intelligence layer hosts the AI skill-matching recommender, the reputation-and-rating engine, and a profile analyzer that interprets free-text skill descriptions. The data layer persists users, skills, sessions, and reviews, while the credit-ledger subsystem maintains wallets, records transactions, and manages escrow and settlement.

B. Matching and Exchange Algorithms

The recommender represents each member by the skills they offer and seek, derived from structured tags and free-text analysis. Content-based similarity scores candidate mentors against a learner's requested skill, while collaborative signals incorporate the preferences of similar members; the two are blended into a hybrid ranking that mitigates cold-start. The exchange protocol places the agreed credits into escrow when a session is booked, releases them to the mentor upon completion and rating, and updates both parties' reputation. This escrow step is the mechanism that enforces reciprocity and discourages non-completion.

C. Technologies and Design Decisions

Python anchors the recommender, reputation, and ledger logic owing to its data and machine-learning ecosystem, while Node.js delivers a responsive marketplace and real-time chat. Treating credits as escrowed obligations rather than instantaneous transfers was a deliberate decision to protect both parties and to make reciprocity structural rather than merely encouraged. The reputation engine was integrated directly into the settlement path so that trust signals update automatically with each completed exchange.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.066 ⁒ Peer-reviewed & Refereed journal ⁒ Vol. 13, Issue 6, June 2026

DOI: 10.17148/IARJSET.2026.13639

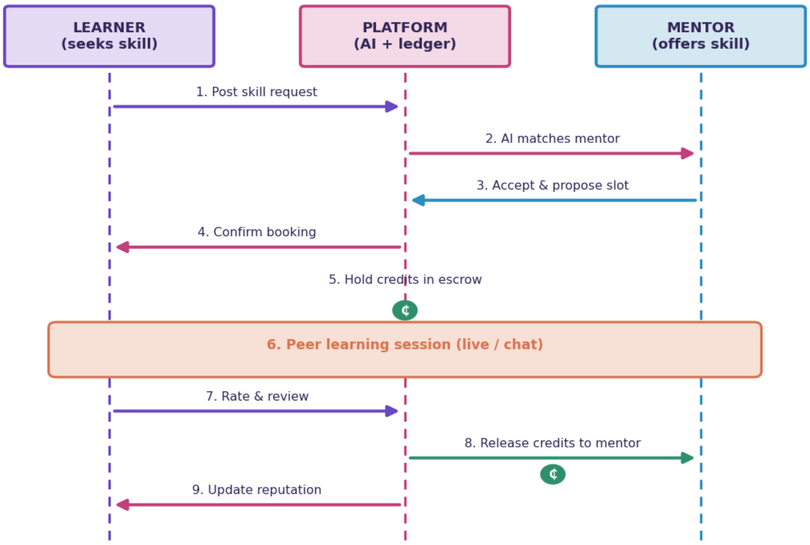

Fig. 2. Interaction workflow among learner, platform, and mentor, showing AI matching, credit escrow, the session, and final settlement with reputation update.

Fig. 2 depicts the exchange as an ordered interaction among the learner, the platform, and the mentor. A request triggers AI matching; upon mutual confirmation the platform escrows credits; the peer session takes place; and after rating, credits are released and reputation is updated, closing the cycle fairly.

4. SYSTEM DESIGN

The system is organized as cooperating modules around a central platform core, as shown in Fig. 3. The core mediates all interactions, while specialized modules handle profiles, matching, reputation, credits, sessions, and notifications.

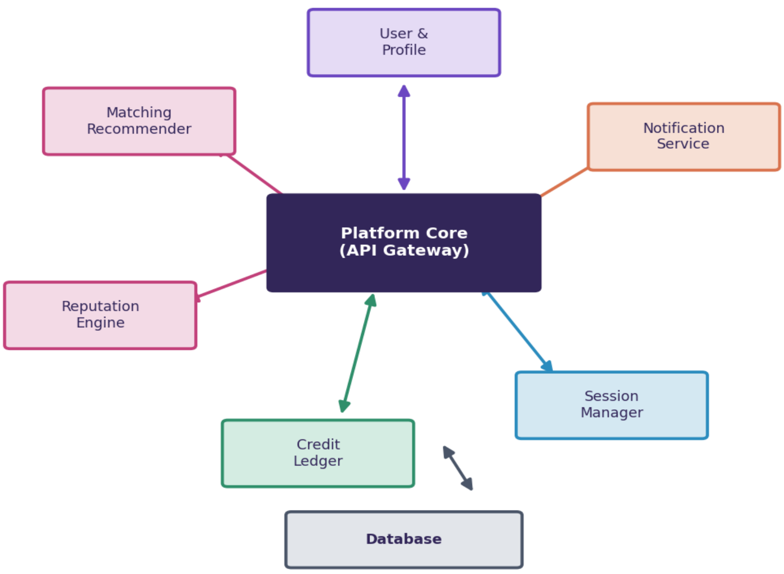

Fig. 3. Module interaction diagram with the platform core mediating the profile, matching, reputation, credit-ledger, session, and notification modules.

A. Module Descriptions

- User and Profile Module: manages registration, skill profiles, and free-text descriptions consumed by the matcher.
- Matching Recommender: produces ranked mentor suggestions using the hybrid algorithm.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.066 ⋇ Peer-reviewed & Refereed journal ⋇ Vol. 13, Issue 6, June 2026

DOI: 10.17148/IARJSET.2026.13639

- Reputation Engine: aggregates ratings into trust scores that inform ranking and display.
- Credit Ledger: maintains wallets and performs escrow, transaction, and settlement operations.
- Session Manager and Notification Service: handle booking, live or chat sessions, and timely alerts to participants.

B. Data and Control Flow

Requests enter through the platform core, which invokes the matcher and reputation engine to assemble recommendations. Upon booking, the core coordinates with the credit ledger to escrow credits and with the session manager to schedule the meeting; after completion, settlement and reputation updates propagate back through the core to the data layer.

5. IMPLEMENTATION

The prototype was developed on a workstation running a 64-bit operating system with a multi-core CPU and 16 GB RAM. The recommender, reputation, and ledger services were implemented in Python 3.11 using data-science and machine-learning libraries, while the marketplace, profile, and chat interfaces were built on Node.js with Express and real-time messaging. Skill profiles, sessions, reviews, and credit transactions were persisted in a relational store, with the ledger tables designed to record immutable transaction history. Table II contrasts the chosen stack with conventional alternatives.

TABLE II. TECHNOLOGY STACK AND RATIONALE VERSUS CONVENTIONAL ALTERNATIVES

Component	Chosen Technology	Conventional Alternative	Rationale
Recommender core	Python 3.11 + ML libs	Java / PHP logic	Rich ML and data ecosystem
Interface layer	Node.js + Express	Server-rendered pages	Responsive, real-time UX
Matching	Hybrid recommender	Single-strategy filter	Mitigates cold-start
Exchange	Credit ledger + escrow	Direct cash payment	Fair, non-monetary reciprocity
Datastore	Relational DB	Flat-file storage	Integrity for transactions

Fig. 4 shows a representative implementation view of the marketplace, including AI-matched mentor recommendations, per-skill match-quality indicators, credit-priced booking actions, and the learner's credit balance.

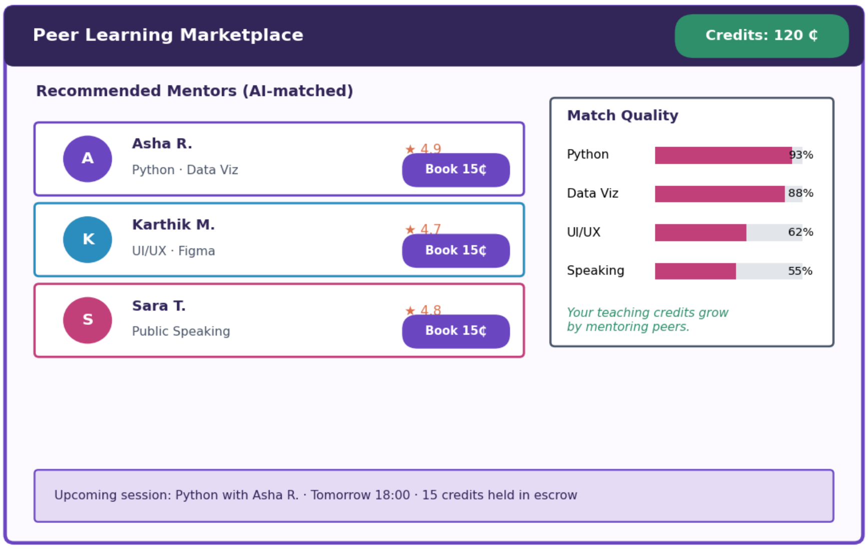

Fig. 4. Implementation view of the marketplace showing AI-matched mentors, match-quality indicators, credit-priced bookings, and the credit balance.

IARJSET

ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.066 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 13, Issue 6, June 2026

DOI: 10.17148/IARJSET.2026.13639

6. RESULTS AND DISCUSSION

The recommender was evaluated on interaction data partitioned into training and testing sets, and platform dynamics were studied through a simulated community over an eight-week horizon. Four recommendation strategies were compared: a popularity baseline, a content-based recommender, a collaborative-filtering recommender, and the proposed hybrid. Recommendation quality was measured by precision-at-five and recall-at-five, and engagement was tracked through completed sessions and circulated credits.

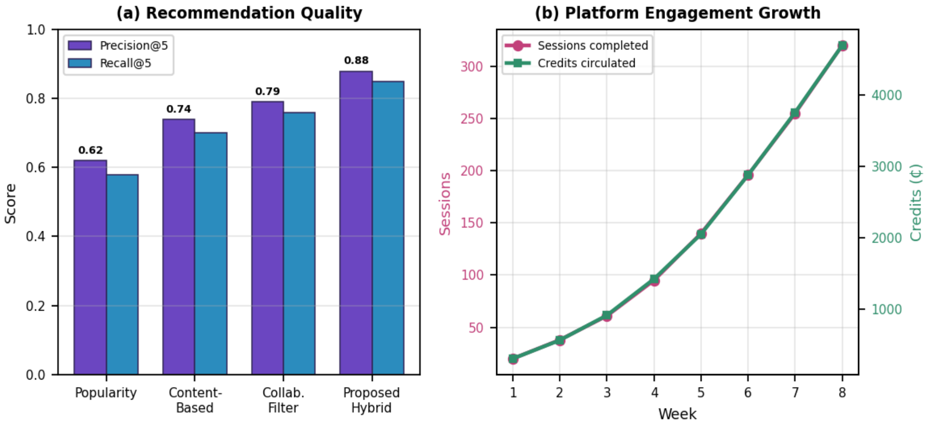

Fig. 5. Performance comparison: (a) precision-at-five and recall-at-five across recommenders; (b) growth in completed sessions and circulated credits over eight weeks.

As shown in Fig. 5(a), the hybrid recommender achieved the best results, with a precision-at-five of 0.88 and recall-at-five of 0.85, exceeding the collaborative-filtering, content-based, and popularity baselines. Fig. 5(b) shows that completed sessions and circulated credits grew steadily as the community matured, indicating a healthy reciprocal economy. Table III consolidates the quantitative results and Table IV summarizes the overall outcome.

TABLE III. RECOMMENDATION PERFORMANCE ACROSS STRATEGIES

Metric	Popularity	Content	Collab.	Proposed
Precision@5	0.62	0.74	0.79	0.88
Recall@5	0.58	0.70	0.76	0.85
F1@5	0.60	0.72	0.77	0.86
Cold-start coverage	Low	Medium	Low	High

Two findings merit emphasis. First, the hybrid strategy's advantage was clearest for new members, where collaborative filtering alone struggled due to sparse histories; blending content-based similarity preserved useful matches during cold-start, a decisive property for a growing community. Second, the credit-with-escrow protocol sustained balanced participation: because credits earned by teaching are needed to learn, members were incentivized to contribute, and escrow reduced non-completion. The baselines, while simpler, neither matched the hybrid's accuracy nor addressed reciprocity, underscoring the value of integrating matching, credits, and reputation.

TABLE IV. SUMMARY OF KEY RESULTS RELATIVE TO COLLABORATIVE-FILTERING BASELINE

Dimension	Collaborative Baseline	Proposed Framework
Precision@5	0.79	0.88 (+0.09)
Cold-start coverage	Low	High
Reciprocity enforcement	None	Credit + escrow
Trust mechanism	None	Reputation engine

DOI: 10.17148/IARJSET.2026.13639

7. ADVANTAGES OF THE PROPOSED SYSTEM

- Technical: a hybrid recommender mitigates cold-start and sparsity, producing accurate bidirectional matches that single-strategy filters cannot.
- Fairness: the credit-with-escrow protocol enforces reciprocity and removes monetary barriers, broadening access to peer expertise.
- Trust: an integrated reputation engine converts session ratings into reliable signals, improving partner selection over time.
- Scalability: the modular, core-mediated design permits horizontal extension—new skills, matching strategies, or interface clients integrate without disrupting the ledger.

8. LIMITATIONS

Recommendation quality depends on community size and interaction density; very small communities limit collaborative signals. The credit economy requires careful calibration of initial balances and pricing to avoid inflation or stagnation of credits. Reputation systems remain susceptible to collusion and rating manipulation, which require ongoing safeguards. Finally, the present evaluation relied partly on simulated activity, so validation with a large live user base remains to be undertaken.

9. FUTURE ENHANCEMENTS

- Incorporate deep representation learning of skills and learner intent to further improve matching beyond tag similarity.
- Add fraud- and collusion-resistant reputation methods, including anomaly detection on rating patterns.
- Introduce group sessions and skill pathways so members can progress through structured, multi-step learning.
- Explore distributed-ledger settlement for transparent, portable credits across federated communities.

10. CONCLUSION

This paper presented a smart peer-learning platform that unifies AI-driven bidirectional skill matching, a credit-based exchange protocol with escrow, and a reputation engine for trust. The hybrid recommender outperformed popularity, content-based, and collaborative-filtering baselines—most notably for new members during cold-start—while the credit-and-escrow mechanism sustained balanced reciprocity and the reputation engine fostered trust among strangers. Together these components transform informal peer learning into an equitable, discoverable, and trustworthy marketplace. Future work will deepen the matching models, harden reputation against manipulation, support structured learning pathways, and explore distributed settlement, advancing toward scalable and inclusive peer-driven education.

REFERENCES

[1] A. Brown and S. Lee, “The rise of informal and lifelong learning in the digital age,” IEEE Trans. Learning Technol., vol. 15, no. 2, pp. 180–194, 2022.

[2] M. Oliveira and K. Singh, “Peer-to-peer learning communities: A systematic review,” Comput. Educ., vol. 190, pp. 1–18, 2023.

[3] R. Topping, “The effectiveness of peer tutoring revisited,” Educ. Psychol. Rev., vol. 33, pp. 1011–1032, 2021.

[4] P. Nguyen and L. Tran, “Barriers to access in commercial e-learning platforms,” Int. J. Educ. Technol. Higher Educ., vol. 18, pp. 1–16, 2021.

[5] D. Roberts and S. Mehta, “Monetization models and equity in online education,” IEEE Access, vol. 10, pp. 60210–60225, 2022.

[6] C. Brown and E. Nilsson, “Reciprocity failures in online exchange marketplaces,” Electron. Commer. Res. Appl., vol. 50, pp. 1–13, 2021.

[7] J. Park and Y. Kim, “Content-based recommendation for educational resources,” IEEE Trans. Learning Technol., vol. 14, no. 4, pp. 510–522, 2021.

[8] Y. Liu, R. Gupta, and H. Zhao, “Collaborative filtering: Advances and open challenges,” ACM Comput. Surv., vol. 54, no. 7, pp. 1–36, 2022.

[9] S. Patel and N. Joshi, “Mitigating cold-start in recommender systems,” Expert Syst. Appl., vol. 198, pp. 1–14, 2022.

[10] H. Nakamura and F. Costa, “Hybrid recommender systems for e-learning,” IEEE Access, vol. 11, pp. 33010–33026, 2023.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.066 ⋇ Peer-reviewed & Refereed journal ⋇ Vol. 13, Issue 6, June 2026

DOI: 10.17148/IARJSET.2026.13639

[11] R. Iyer and M. Fernandes, "Course recommendation using hybrid models," Educ. Inf. Technol., vol. 28, pp. 14010–14030, 2023.

[12] T. Oliveira and S. Banerjee, "Bidirectional matching in two-sided learning platforms," IEEE Trans. Comput. Soc. Syst., vol. 11, no. 1, pp. 220–231, 2024.

[13] G. Martin and L. Schmidt, "Reputation and trust in online marketplaces: A survey," ACM Comput. Surv., vol. 55, no. 9, pp. 1–38, 2023.

[14] A. Verma and D. O'Connor, "Time-banking and non-monetary service exchange systems," IEEE Technol. Soc. Mag., vol. 41, no. 3, pp. 55–64, 2022.

[15] K. Reddy and V. Sharma, "Designing credit-based reciprocity mechanisms," Decis. Support Syst., vol. 160, pp. 1–13, 2022.

[16] P. Lindgren and S. Hassan, "Blockchain ledgers for transparent peer exchange," IEEE Internet Things J., vol. 11, no. 4, pp. 6200–6212, 2024.

[17] M. Zhao and K. Singh, "Representation learning of skills for talent matching," IEEE Trans. Knowl. Data Eng., vol. 37, no. 2, pp. 900–913, 2025.

AUTHORS' BIOGRAPHIES

PASUPULETI PRAMEELA VISALAKSHI received the B.Sc. degree from S.V.K.P. & Dr. K.S. Raju Arts and Science College, Penugonda, West Godavari, India, in 2024. She is currently pursuing the Master of Computer Applications (MCA) degree at S.V.K.P. & Dr. K.S. Raju Arts and Science College, Penugonda, West Godavari, India. Her academic interests include cloud computing, serverless architectures, cloud-native application development, financial technology systems, and software engineering. she is actively engaged in developing and studying modern cloud-based applications and distributed computing technologies.

K. LAKSHMANA REDDY Working as Associate Professor in S.V.K.P & Dr. K.S Raju Arts and Science College(A), Penugonda, West Godavari District, A.P. Master's Degree in Computer Applications from Andhra University 'C' level from DOEACC, New Delhi and MTech from Acharya Nagarjuna University, AP. He attended and presented papers in conferences and seminars. He has done online certifications in several courses from NPTEL. His areas of interest include Computer Networks, Network Security and Cryptography, Formal Languages and Automata Theory and Object-Oriented programming languages.