Data-driven peer recommendation in higher education: A pilot study on academic reading

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Collaborative learning in tertiary education faces challenges such as limited teacher intervention and effective student pairing. This study addresses these issues by proposing a data-driven peer recommendation approach enhanced with learner profile visualisation. The system dynamically matches students based on evolving learning profiles, using an open learner model to improve transparency and decision-making. Implemented in a Japanese university, a pilot study in an academic reading course showed that peer feedback improved report scores, with visualisation aiding in selecting suitable peer reviewers. Comparisons across three recommendation rounds suggested that integrating recursive data accumulation strengthened personalised peer recommendations and encouraged greater participation. By demonstrating the workflow of peer learning implementation, this research also highlights the broader potential of data-driven systems to support collaborative learning in higher education.

Implications for practice or policy:

- Peer review activities with clear criteria can help students revise and improve writing, even within limited rounds.
- Data-driven analytics and recursive evidence accumulation can enable personalised peer recommendations while ensuring inclusivity by mitigating algorithmic biases.
- Visualised reviewer profiles via open learner models may enhance perceived feedback quality and student agency, though more controlled validation is needed.
- Policymakers could support flipped learning models that leverage data-driven personalised recommendations to enhance learner autonomy and peer collaboration.

Keywords: peer recommendation, academic reading, open learner model, peer feedback, higher education, data-driven

Introduction

Collaborative learning has gained significant importance in tertiary education (Sidhu & Gage, 2021), as collaboration is widely recognised as a critical 21st-century skill essential for success in modern society (Jacobs & Seow, 2015). Unlike in K-12 education, where students frequently interact with a stable peer group, university students often lack familiarity with their classmates, resulting in limited social interaction, which can hinder the development of collaborative skills. Consequently, educators have increasingly resorted to flipped and collaborative learning strategies to address these challenges. These approaches are particularly well suited to university students, who typically possess greater maturity and self-regulated learning capabilities (Bergmann & Sams, 2012).

Peer tutoring, as a prominent practice within collaborative learning, has become a widely adopted strategy (Chu et al., 2017). However, in traditional learning environments, instructors often struggle to effectively pair students for peer learning activities due to limited insight into their strengths and weaknesses (Gogoulou et al., 2007). This issue is further exacerbated in tertiary education, where high student mobility complicates the formation of stable peer networks. Additionally, maintaining student engagement in tertiary education, particularly during lengthy 90-minute classes, remains a persistent challenge. Traditional lecture-based methods, which rely on one-way content delivery, often fail to sustain student interest and active participation. This underscores the need for more flipped and student-centred approaches to teaching (Acarol, 2019; Collaço, 2017).

Academic reading, a fundamental skill for undergraduate students, presents challenges in higher education. For non-native English speakers, especially in Asian contexts such as Japan, these challenges are amplified by linguistic and cultural barriers inherent to engaging with English academic texts (Koizumi et al., 2022). Students often struggle with selecting appropriate papers, understanding complex academic expressions and synthesising information to form their own perspectives (Jimenez et al., 2024). Addressing these challenges requires innovative teaching strategies that can effectively support students in acquiring these skills.

To foster interactive and personalised learning in academic reading, this study introduced a data-driven peer recommendation approach enhanced with visualisation tools. Going beyond work that treated peer recommendation (Elghomary & Bouzidi, 2019) and open learner models (Brusilovsky, 2024) separately, this study advances the peer learning field by integrating three essential yet rarely combined elements: (a) a data-driven peer recommendation mechanism that adapts to learners' evolving knowledge profiles, (b) visualisation-based open learner models that support transparency and (c) a system design that fosters autonomous selection.

The proposed mechanism dynamically matches students by aligning with students' evolving knowledge profiles, thereby optimising interaction quality and learning outcomes. The integration of open learner models through visualisation interfaces enhances transparency in recommendation logic, allowing students to make informed peer selection choices while maintaining system accountability, which is critical in building explainable educational technologies (Khosravi et al., 2022).

Theoretical foundations

Collaborative learning and peer learning

Collaborative learning is a process in which two or more individuals work together to learn or achieve a shared learning goal (Duran & Miquel, 2019). This approach emphasises learner interaction as a key mechanism for improving academic performance and developing social skills (Topping, 2005). Among the various collaborative learning strategies, peer learning, such as peer tutoring and peer review, has gained recognition as an effective method (Amjad & Zia, 2025; Topping, 2005). In peer learning communities, learners often assume dual roles as both tutors and tutees, fostering mutual learning and deepening their understanding of the subject matter (Dooley & Bamford, 2018). Moreover, mutual evaluation is a critical component of peer learning, with approaches such as backward evaluation designs being implemented to assess the effectiveness of these interactions (Misiejuk & Wasson, 2021).

The theoretical underpinnings of peer learning are rooted in Vygotsky's (1978) concept of the zone of proximal development (ZPD). The ZPD refers to the range of tasks that learners can accomplish with guidance but cannot yet perform independently. Scaffolding, as an instructional strategy, provides temporary support to help learners bridge the gap between their current abilities and their potential. Peer learning operationalises this concept by pairing learners with peers who can provide the necessary scaffolding during collaborative activities.

In computer-supported learning environments, peer learning can be further enhanced through structured interactions and tailored scaffolding (Baruah et al., 2019). By leveraging recommendation algorithms, it becomes possible to identify peers who fall within a learner's ZPD, thereby facilitating productive and equitable peer learning. This approach requires profiling the learner's knowledge attributes to enable accurate and effective recommendations.

In tertiary education, where learners lack fixed peer groups as they do in primary or secondary schooling, fostering social interaction assumes heightened significance. The social-emotional aspect of learning has emerged as an enduring priority in contemporary society (Erstad et al., 2024), and higher education institutions increasingly emphasise accessible platforms for meaningful interpersonal engagement. Such platforms not only enhance academic performance but also foster the growth of social networks, offering learners dual advantages that extend beyond the classroom. These dual benefits underscore the importance of integrating education technology into peer learning contexts within tertiary education, an area that warrants greater scholarly and practical attention.

Knowledge and learner models

Learning analytics (LA) has gained significant popularity as a method for estimating learners' states by analysing their activities on e-learning platforms (Ferguson, 2012). LA is increasingly focusing on knowledge (Fischer et al., 2002), with educational applications relying on knowledge modeling to represent the relationships between learners, content and tasks (Soumya & Krishnamoorthy, 2025; Takii et al., 2024). Knowledge maps and graphs have proven to be effective tools for visualising these connections, enabling more personalised and adaptive learning experiences (Zhang et al., 2023).

The concept of open learner models has gained traction as a means of increasing transparency and promoting self-regulated learning (Hooshyar et al., 2020; Soumya & Krishnamoorthy, 2025). Open learner models allow learners to view their own progress and proficiency levels, encouraging self-reflection and goal setting. This is particularly important in tertiary education where learners' motivation is more internally driven (Sogunro, 2015). Open learner model visualisations can be applied into assorted educational applications (Brusilovsky, 2024). For instance, when incorporated into recommendation systems, open learner models can provide deeper insights into candidate profiles, supporting more rational and informed decision-making. This transparency can also helps reduce biases and build trust in the system (Winne, 2021).

Research gaps in peer recommendations

Current recommendation systems in education employ machine learning to personalise learning and reduce information overload. However, as illustrated in Figure 1, they face a critical challenge of balancing dynamic recommendations with equitable user participation (Khanal et al., 2020). Systems based on collaborative filtering or optimised for click-through rates prioritise adaptability (Chen et al., 2018; Guo et al., 2024) but often neglect fairness, disproportionately favouring a small subset of high-performing individuals due to sparsity problems (Marcuzzo et al., 2022). For instance, Guo et al. incorporated learner similarity, trust from commonly rated courses and temporal weighting based on rating timeframes to recommend personalised learning resources on online platforms. This strategy, originating in the e-commerce domain, has matured in recommending objective materials but is less suited to recommending human partners for peer learning.

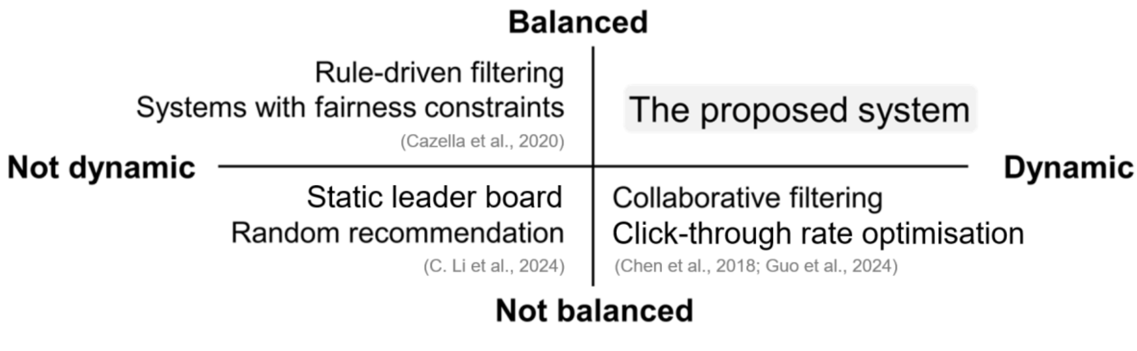

Figure 1. Balancing rule-based fairness and adaptive dynamics: A research gap in recommendation systems

In contrast, rule-driven systems or those with rigid fairness constraints promote balanced participation but lack the flexibility for dynamic learner states. For example, Cazella et al. (2020) designed competency-based rules to filter learning objects according to required skill development. Similar logic can be applied to limit peer recommendations for individuals who are over-selected. Although static methods, such as leader boards or random assignments, benefit learning motivation, engagement and performance through gamification (C. Li et al., 2024), they can fail to meet either criterion, making them ineffective for meaningful recommendation interpretations.

In addition, studies utilising educational big data, such as Elghomary and Bouzidi (2019), have focused on interaction logs and friendships in massive open online courses, while Potts et al. (2018) enabled self-reported pairing criteria. However, less attention has been given to learners' knowledge profiles derived from objective daily learning records. These limitations have led research to focus primarily on technical optimisations, often relying on data collected in controlled laboratory settings. As a result, many systems remain underutilised in authentic classroom environments with real students, limiting their practical applicability and scalability in educational contexts.

By integrating these theoretical insights and technological innovations, this study aimed to take a step forward in addressing this gap. Specifically, it optimises recommendations through iterative data accumulation (dynamic), enhancing matching accuracy, while reducing over-reliance on high-performing students to promote balanced participation (balanced). Grounded in established principles of peer learning, the system's pilot implementation sought to demonstrate the potential of data-driven methods to enhance peer learning outcomes in tertiary education.

Infrastructure and algorithm of peer recommendation

Data source and infrastructure

Data that describe learner characteristics are indispensable for data-driven recommendation systems. To construct a comprehensive learner profile, the proposed peer recommendation approach integrates established systems and conceptual frameworks. As illustrated in Figure 2, the technical framework outlines the backbone of the system.

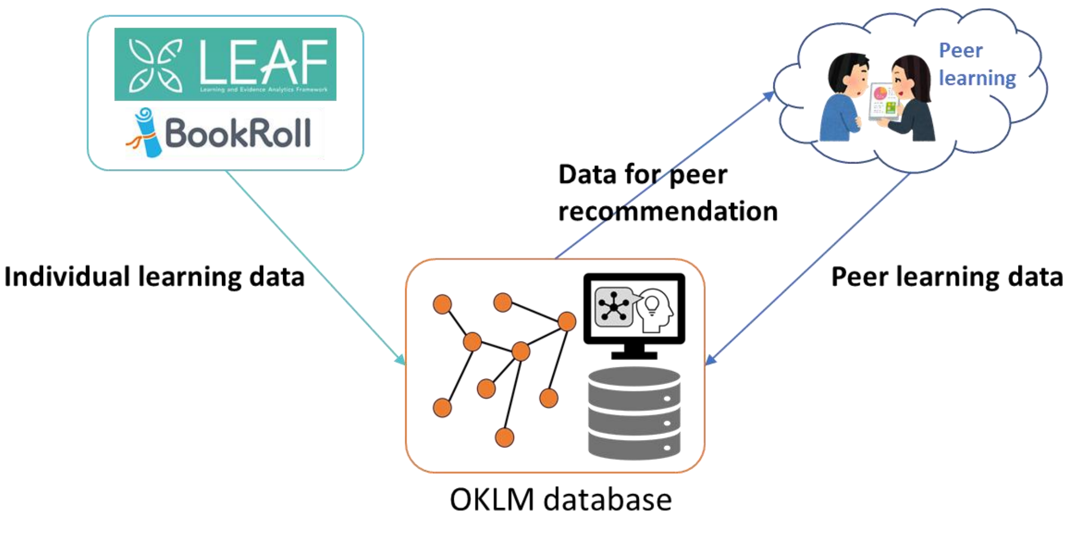

Figure 2. The backbone of the system infrastructure

The peer recommendation system is powered by the open knowledge and learner model (OKLM; Takii et al., 2024), a graph database designed to manage knowledge-based data from digital learning platforms. OKLM connects a knowledge model and an open learner model, which establishes relationships between learners' daily learning activities and the knowledge units they interact with, utilising graph-based modelling to represent knowledge relationships and learners' proficiency levels. This enables a deeper understanding of learners' knowledge states.

As depicted in Figure 3, nodes in OKLM represent knowledge units (K) and learners (L), and the edges between nodes define the relationships. As an open knowledge model, knowledge nodes can represent various types of interconnected knowledge depending on the context. Examples include English vocabulary (Takii et al., 2024), computer science topics (Brusilovsky, 2024; Soumya & Krishnamoorthy, 2025) and academic literature, which will be further discussed later. Relationships can be simplified into two types: These connections illustrate both the relationships between knowledge units (K-K) and learners' overall proficiency with them (L-K).

Currently, the primary data source for OKLM is the learning evidence and analytics framework (LEAF; Ogata et al., 2024), a comprehensive LA platform designed to collect and analyse data from learning support systems. LEAF has been adopted in over 20 universities and K-12 schools in Japan, as well as in more than eight countries worldwide, demonstrating its scalability and cross-cultural applicability.

A key component of LEAF in this process is BookRoll, an e-book platform that tracks learners' interactions with digital learning materials (Ogata et al., 2015). Through BookRoll, learners can perform various actions such as navigating pages, adding annotations and bookmarking sections, all of which are logged in real time. Among these logs, knowledge-based behaviours are further integrated into the OKLM database via xAPI statements. For example, in English learning, vocabulary highlighted with markers or used in memo notes is linked to corresponding vocabulary nodes in OKLM. Similarly, engagement with academic papers can be mapped to an academic literature network. These indicators of individual learning performance are incorporated as the baseline input for the recommendation algorithm, referred to as *$Proficiency_i$*.

Recursive recommendation

The group learning orchestration based on evidence (GLOBE) framework (Liang et al., 2024) is a data-driven model to support collaborative learning through four phases: group formation, orchestration, evaluation and reflection. By integrating LA and collaborative learning log data, GLOBE facilitates group learning activities in digital environments. The framework emphasises the iterative refinement of group learning outcomes by continuously accumulating data throughout the collaborative learning process, which informs subsequent implementation cycles. The peer recommendation approach builds upon GLOBE’s data-driven principles, structuring its data flow to enhance both learning performance and learner model development. A mutual evaluation mechanism is embedded in the recommendation system, where the help seeker is prompted to rate the quality of the assistance received from the help provider, and the provider can rate how much the help seeker improve after receiving the assistance.

The evaluation mechanism serves a dual purpose: it assesses the benefits gained by the help seeker and reflects the feedback provider’s ability to enhance their own understanding. Based on this, two key metrics are used to update the learner models of the participants:

- *$Proficiency_p$* (for help seeker): This metric captures the knowledge gain of learners who seek help during peer interactions beyond that in individual learning ($Proficiency_i$).
- *Comprehension* from clarification (for help provider): This metric reflects the knowledge gain of help providers when clarifying the solutions to others.

Learners with high proficiency and comprehension scores on certain knowledge are all prioritised for future recommendations, valuing both understanding level and ensuring the system values both knowledge depth and communication skills. This iterative learner model captures the collaborative and dynamic nature of peer learning, extending beyond individual learning logs.

Knowledge graph-based algorithm

To recommend suitable peers in pairwise learning activities, the algorithm identifies appropriate helpers by analysing the knowledge network and assessing their proximity to the asker’s problem domain. It incorporates three key indicators, $Proficiency_i$, $Proficiency_p$ and Comprehension, to compute a recommendation score for each potential helper.

As illustrated in Figure 3, the algorithm searches the knowledge network to identify all knowledge units associated with a potential helper. For each of these units, it calculates the shortest path to the knowledge nodes included in the problem space of the help seeker's question, which may consist of multiple nodes or a single unit. The Distance attribute, defined as the number of edges in this shortest path, quantifies the connection strength, where greater distances indicate weaker associations. For each knowledge node included in the problem space, the system computes a recommendation score for each knowledge unit connected with the helper candidate using the following formula (1), where *w* indicates *w*eights assigned to the three indicators, constrained such that $w_1 + w_2 + w_3 = 1$.

$$\text{knowledge\_score} = \frac{w_1 \cdot Proficiency_i + w_2 \cdot Proficiency_p + w_3 \cdot Comprehension}{Distance} \quad (1)$$

$$\text{recommendation\_score} = \sum \text{knowledge\_score} \quad (2)$$

The total recommendation score is calculated by summing all knowledge scores for each potential helper as formula (2). The system then ranks candidates based on these scores, presenting several highest-ranked candicates. To enhance adaptability, teachers can customise the weights of the three L-K indicators to align with specific educational objectives. This flexibility allows the recommendation system to be tailored to diverse learning scenarios and pedagogical goals.

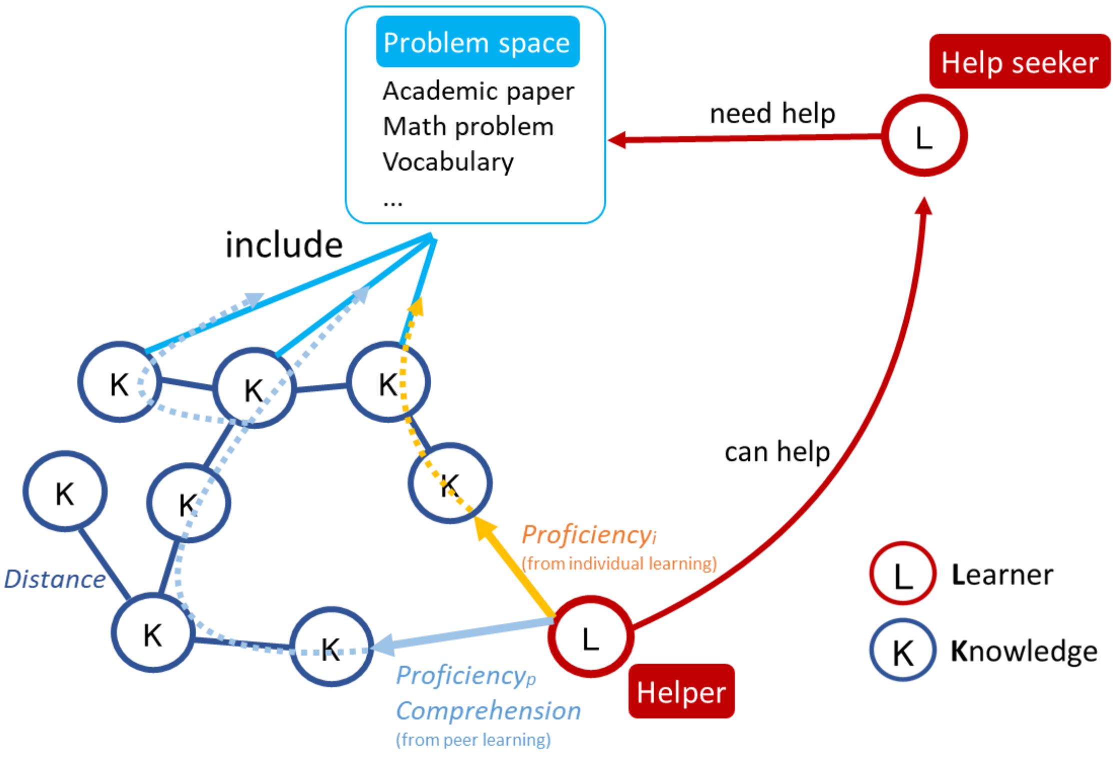

Figure 3. General peer recommendation mechanism in the OKLM structure

Autonomous selection with OKLM visualisation

As depicted in Figure 4, the peer recommendation system does not determine the final help provider solely based on the algorithm. Instead, it provides users with the flexibility to choose from a range of candidates, guided by the OKLM visualisation. The help provider selection interface visualises the OKLM structure using a knowledge graph, which includes the following features:

- Nodes represent related knowledge units. In Figure 4, each node represents an academic paper.
- Hovering over a node reveals the name of the corresponding knowledge unit, offering additional context (see the grey box).

- Each node displays a numeric value indicating the helper's expected proficiency for that specific knowledge unit.
- The knowledge unit selected by the asker is highlighted with a red circle, making it easy to identify the focus of the peer-help activity.

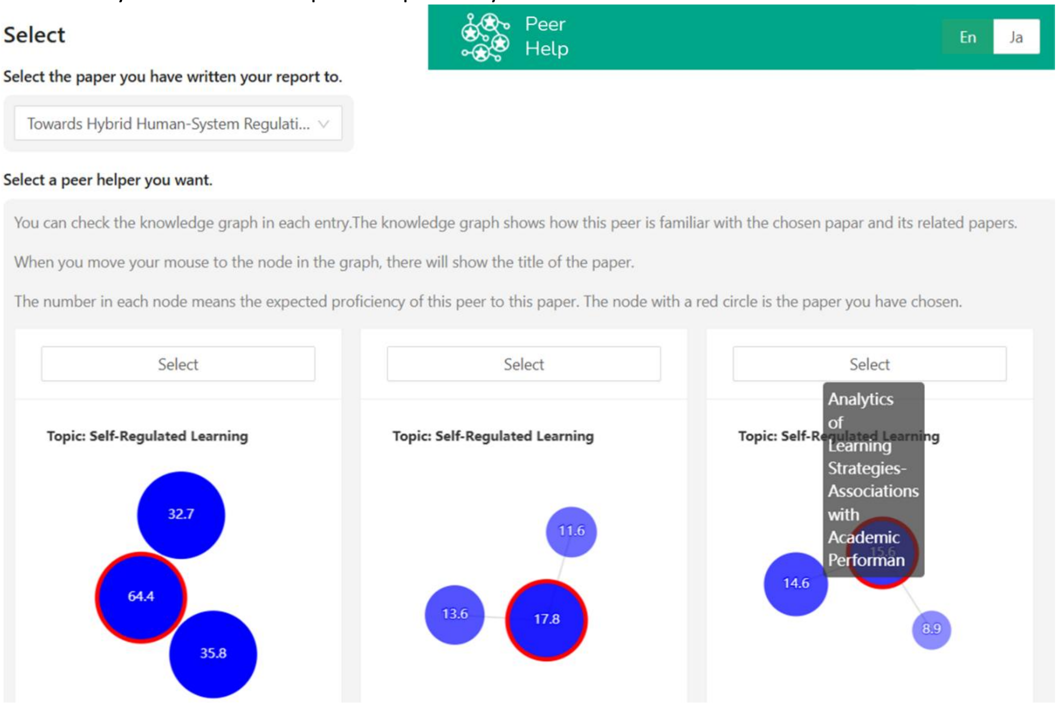

Figure 4. The main interface of peer recommendation with OKLM visualisation function (interface available in both Japanese and English depending on browser language settings)

As an open learner model, the visualisation was designed to improve the interpretability of the recommendation algorithm, empowering askers to make informed decisions when selecting helpers (Jugovac & Jannach, 2017). Although the system provides recommendations, the visualisation ensures that help seekers retain autonomy in their choices (Hoppe & Ploetzner, 1999). For instance, one learner might prioritise a helper with balanced proficiency across all related knowledge units, while another might focus on a helper with exceptional expertise in the selected knowledge unit of interest.

In addition, the visualisation design ensures anonymity by concealing the identity of helpers during the selection process. This approach encourages objective decision-making based solely on the knowledge graph, mitigating biases arising from personal or social factors and fostering a fair and equitable selection process.

Pilot implementation in university

The academic paper reading course, a common component of liberal education in Japanese universities, provided an ideal setting for the pilot implementation of the peer recommendation system. This course is designed to equip undergraduates with the foundational skills needed to read and analyse academic papers in English.

As an imperative aspect of academic communication, peer review activities play a vital role in this course. They provide students with opportunities to engage in constructive critique and receive instructional feedback from diverse perspectives. This process fosters an interactive learning environment and levels a playground for deploying the proposed peer recommendation system. Therefore, this pilot study was guided by the following research questions (RQs) within the context of academic reading:

- RQ1: To what extent does peer feedback, facilitated by the recommendation system, enhance learning performance?

- RQ2: How does the accumulation of peer-help activity data contribute to the quality of feedback and its impact on learning outcomes?
- RQ3: Does the OKLM visualisation improve users' ability to identify suitable peer reviewers?

Overview of the course

A total of 31 students enrolled in the academic reading course of a Japanese national university during the 2024 academic year, with 29 successfully completing the course. The course was conducted primarily in English, with supplementary explanations provided in Japanese. The majority were second-year students from various subdivisions of the Faculty of Engineering, along with two students from other faculties such as the Faculty of Integrated Human Studies. The course was structured into two main phases: a 5-week lecture series, followed by three intensive reading projects spanning the subsequent 9 weeks. The academic papers used in the course were selected from open-access articles published in the 2019 Learning Analytics and Knowledge conference. A literature network was manually constructed based on the conference session themes of each paper, as outlined in the official proceedings (Azcona & Chung, 2019).

During the first 5 weeks, instructors delivered lectures and guided practice tasks to introduce the fundamentals of academic reading. This phase aimed to equip learners with foundational academic reading skills, preparing them for the more advanced and interactive tasks in the latter half of the course. The second phase focused on practical application, with the peer recommendation system serving as a central component across three structured peer review-oriented sessions. The workflow for each session in the second phase, as illustrated in Figure 5, followed a consistent 3-week procedure to ensure a standardised approach to peer learning.

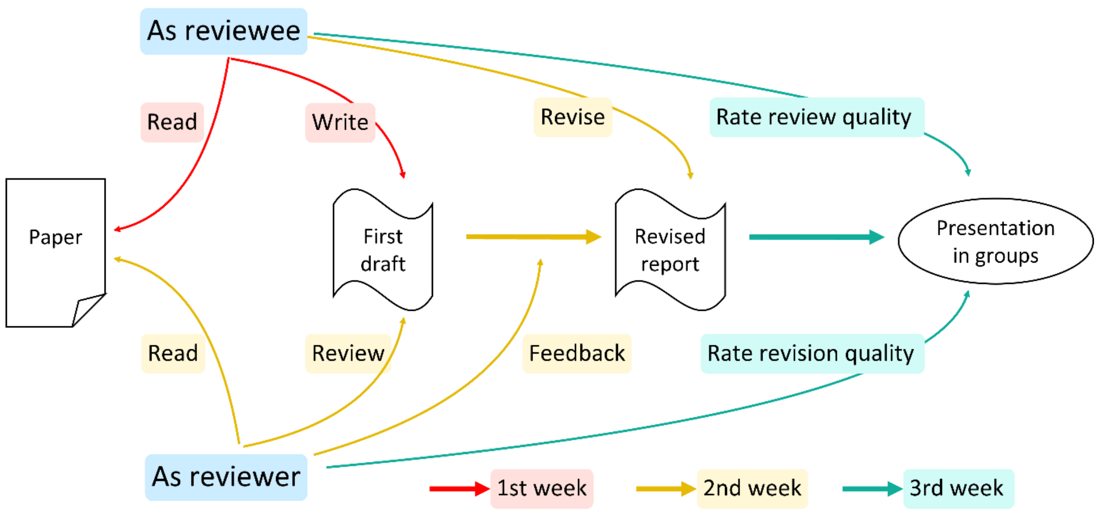

Figure 5. Process of 3 weeks' tasks in one peer review session

In the first week of each session, learners selected a paper from a pre-defined list provided by the instructor. They thoroughly read the chosen paper and composed a report following the reading guidelines adapted from the peer review principles in the accompanying Wiley Author Services website.

During the second week, students engaged in a structured peer review activity. Following the submission of their first-week assignment drafts, students were paired via the peer recommendation system. In this scenario, each student assumed dual roles: (a) a help provider, referring to the student acting as a reviewer, offering constructive feedback on their peer's work; (b) a reviewee, denoting a student requesting peer review feedback on their first draft and subsequently revising their report based on the reviewer's input. The peer reviews were also guided by the evaluation criteria outlined in Table 1.

The third week focused on presentations and evaluations. Each student presented their revised report within small groups, emphasising how they incorporated the feedback received from their help provider.

Following the presentations, at the end of the activity, learners were required to use backward evaluation to provide mutual feedback. These evaluation results were recorded as indicators of the peer-help activity and contributed to improving recommendations in future activities.

Table 1
Guidelines for academic reading report

Construct	Question (originally in English with Japanese translations presented for clarity)
Summary	What is the research question of this paper?
	What experimental procedures were mentioned, what techniques were used and what theories were used in this paper?
	What results were obtained in this paper and how were they analysed?
	What is the innovation of this paper or the main contribution of this paper?
Discussion	Is computer technology used effectively in teaching?
	Do you think the paper's methodology and data support the results, or are there any logical problems or limitations not mentioned by the authors?
	Are there any ethical issues not mentioned by the authors?
	Is there a need to adjust this paper's narrative order or structure?
	What do you think is related to your study or research?
	What parts of this paper did you have difficulty understanding?

Workflow for pairing system under the peer recommendation

The peer recommendation module was embedded into the LEAF infrastructure and deployed within the Moodle learning management system in the university setting. Before the peer review activity, learners engaged in individual reading using BookRoll, where they accumulated a baseline level of knowledge proficiency. This individual learning data served as the cold-start input for the subsequent peer recommendation process. The instructor then initiated a new peer review activity in LEAF to facilitate peer matching.

To ensure equal participation, pairwise matching was implemented: each learner selected one feedback provider from a list of five top-ranked candidates and, in turn, was chosen as a reviewer by another learner within the same round of peer-help activities. This design ensured that every participant engaged in both the seeking and providing of help within each session.

Upon entering the peer review activity in LEAF, learners first entered the reviewer selection interface (see Figure 4). Reviewees specified the knowledge unit, corresponding to the paper they read that week. After the matching process, learners could view both their selected reviewer and the peer who had chosen them as a reviewer. Prior to the pairing activity, the instructor uploaded all first-draft reports to BookRoll. Students could begin peer review immediately after confirming their pairs, utilising the marker and memo functions within the e-book platform to provide textual feedback. Simultaneously, they could view their reviewers’ annotations on their assignments through the BookRoll dashboard.

The data source for peer recommendation evolved across sessions. Although the first session relied exclusively on proficiency data from BookRoll, the second and third sessions incorporated both proficiency and comprehension metrics derived from earlier rounds of peer review activities. In this study, all three input indicators were assigned equal weight.

Data collection

To address the RQs, data were collected from multiple sources, including the course gradebook, LEAF system logs and Moodle-based questionnaires. This research work included human participants, and their participation was reviewed and approved by the university’s Ethics Committee. All students whose data were included in the analysis provided informed consent in paper-based form, agreeing to the use of their anonymised data for research purposes. The data collected included:

- BookRoll learning logs: Metrics such as reading time, number of markers and number of memos were recorded. These engagement behaviours were integrated and normalised into a proficiency score Proficiencyi, ranging from 0 to 1, calculated as the average of these metrics.
- Report scores: The instructor evaluated both the first and revised drafts of intensive reading reports for each session based on the guidelines in Table 1. Scores were assigned on a 20-point scale.
- Mutual ratings of the peer review: Peer ratings updated two key metrics: (a) improvement in the revised report, assessed by the reviewer, updated the Proficiencyp of the reviewee and (b) review quality scores, provided by the reviewee, updated the comprehension metric of the reviewer. (Numerical ratings were fully anonymised and visible only to the instructor and the backend recommendation system. Students were informed of this arrangement when the system was introduced at the beginning of the course.)
- Short survey on visualisation: After each intensive reading session, a binary question asked whether participants interacted with the OKLM visualisation when selecting a reviewer from the recommended candidates.
- Final questionnaire: A semester-end survey collected participants' perceptions and usability feedback on the peer recommendation system, using a 5-point scale.

Data analysis and results

RQ1: Educational implication

The first RQ aimed to assess the educational implications of the peer feedback activity within the peer recommendation mechanism. Because the difference scores violated normality in all three sessions ($p < .001$ by Shapiro-Wilk test), we employed Wilcoxon signed-rank tests. The mean score of the report content increased by 1.03, 0.73 and 0.72 after Sessions 1, 2 and 3 respectively ($p < .001$). Each session showed a statistically significant gain with a large effect size ($r > .50$). Table 2 indicates the descriptive statistics of the report scores in three sessions.

Table 2
Comparison of original and revised report scores for three sessions

Session	Report type	N	Min	Max	Mean	SD	Wilcoxon V	Effect size *r*
1st	Original report score (0–20)	31	3	15	7.23	3.01	171.0***	0.66
	Revised report score (0–20)	31	4	15	8.26	2.84		
2nd	Original report score (0–20)	30	2	13	7.80	2.91	153.0***	0.66
	Revised report score (0–20)	30	2	14	8.53	3.10		
3rd	Original report score (0–20)	29	1	13	6.90	3.14	91.0***	0.58
	Revised report score (0–20)	29	2	14	7.62	3.13		

***$p < 0.001$

To further explore the role of peer feedback in score improvement, Spearman's rank correlation coefficient was calculated to assess the relationship between the perceived review quality scores (rated on a 1–5 scale by reviewees, with 1 meaning *no review received*) and the report score difference after revising in each session. Spearman's method was chosen because the perceived quality score is an ordinal variable, and both variables violate normality. The results are summarised in Table 3. The sample size reduced as some students did not finish the mutual rating after the session. In the first session, there was a tendency of positive correlation ($p = .063$) between the review quality scores and the report score difference. However, in the second and third sessions, no significant difference was detected.

Table 3
Comparing rating of feedback quality and report score difference for three sessions

Session	Measure	N	Min	Max	Mean	SD	ρ
1st	Perceived review quality	29	1	5	4.00	1.31	0.35
	Report score difference	29	0	6	1.00	1.36	
2nd	Perceived review quality	27	1	5	3.81	1.30	0.06
	Report score difference	27	0	2	0.59	0.64	
3rd	Perceived review quality	26	1	5	3.96	0.96	-0.292
	Report score difference	26	0	5	0.69	1.19	

RQ2: Effectiveness of data-driven design

The second RQ examined the effectiveness of the system's data-driven design by comparing learning outcomes across three peer review sessions, with the first session serving as a baseline. We hypothesised that as proficiencyp and comprehension data accumulate recursively, the open learner model would capture student characteristics more accurately, thus leading to improved peer recommendations and higher-quality feedback, and ultimately better learning outcomes.

To assess this, we analysed variations in report scores and word counts across the three peer review sessions. A rise or fall in word count could reflect positively or negatively on outcomes and amendments made to a paper following peer review. Shapiro-Wilk tests indicated non-normality in score differences ($p < .001$), though Levene's test confirmed equal variances ($p = .530$). Due to the non-normal distribution of the data, a Kruskal-Wallis test revealed no significant differences in report score variation between sessions ($H = 1.165$, $p = .558$). Similarly, a Kruskal-Wallis test found no significant difference in word count changes (deviated from normality, $p < .001$ in Shapiro-Wilk test) following peer review ($H = 0.946$, $p = .623$).

Figure 6 presents the Sankey diagram illustrating transition patterns in word count changes. The threshold between the low and mid categories was determined by whether the reviewee made any revisions, while the threshold between the mid and high categories (13 words) was set at the median word count change across all participants in all sessions. The results indicate an increase in word count modifications from the second to the third session, with nearly 45% of students making more extensive revisions and reaching the "high" category. Notably, no students remained entirely disengaged in revision after three rounds of peer recommendation-facilitated peer review. However, some students continued to fluctuate, occasionally falling into the low-engagement group.

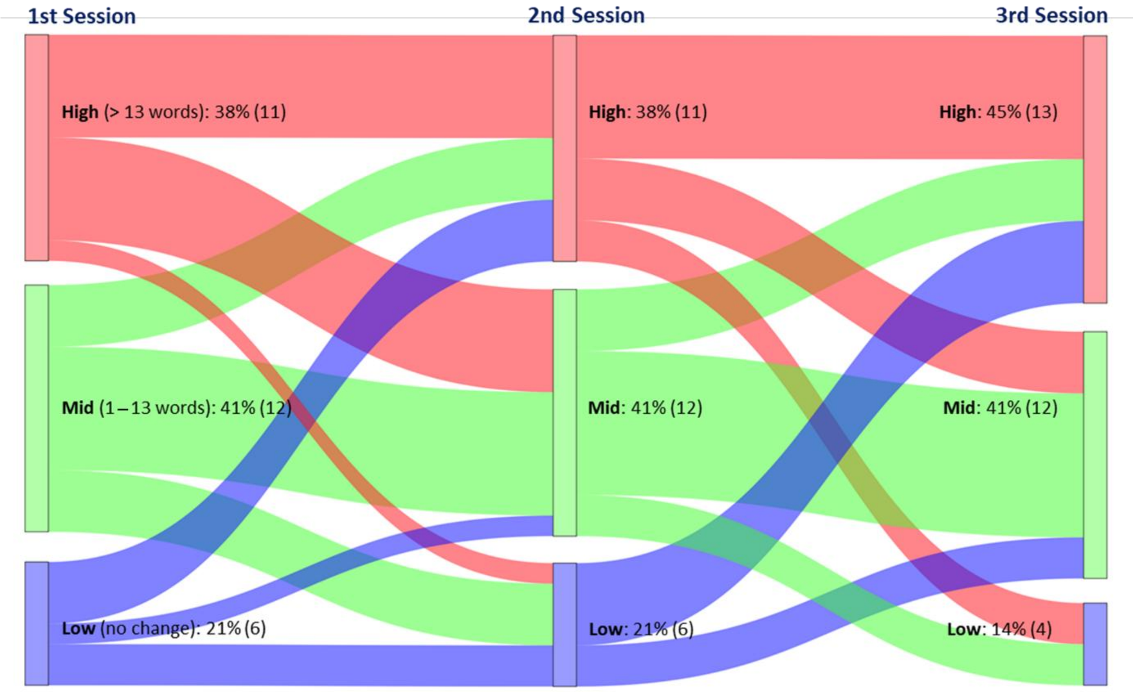

Figure 6. Sankey diagrams for word count changes across three sessions

RQ3: Effect of OKLM visualisation

The third RQ investigates whether the visualisation feature enhances the system's usability by assisting students in identifying suitable reviewers who provide high-quality feedback. To inspect this relationship, we conducted a Mann-Whitney *U* test on aggregated data from all three sessions, comparing the review quality scores reported by students as reviewees between those who used the OKLM visualisation and those who did not. A Shapiro-Wilk test revealed that the quality scores in both groups significantly deviated from normality ($p < .001$), justifying the use of a non-parametric test. As summarised in Table 4, the results indicate a statistically significant association ($p = .046 < .05$) between visualisation usage and higher review quality scores with a small effect size ($r = .21$).

Table 4
Comparison of review quality scores based on OKLM visualisation usage

	N	SD	Mean	U statistic	Effect size
Viewed	61	1.22	4.08	464.5*	0.21
Did not view	21	1.44	3.52		

*$p < 0.05$

Voice from participants

The final questionnaire on the peer recommendation system revealed mixed but generally positive perceptions across different dimensions. When asked whether they would use the system to seek reviewers in other academic contexts, 55% (44% *agree*, 11% *strongly agree*) expressed willingness, while 30% were neutral and 11% disagreed. In contrast, fewer participants (44%) showed interest in becoming reviewers (*agree*: 37%, *strongly agree*: 7%), with 23% explicitly disagreeing.

Perceived usability was notably high, with 78% finding the system easy to use (*agree*: 59%, *strongly agree*: 19%). However, opinions on the clarity of proficiency visualisation graphs were more divided: 41% found them understandable (*agree*: 30%, *strongly agree*: 11%), while 22% disagreed and 33% remained neutral.

Open-ended feedback suggested potential applications beyond the study's scope, such as peer review for academic writing (e.g., essay drafting, report editing) and cross-disciplinary feedback. Respondents valued the system's ability to provide objective evaluations from diverse perspectives and recommended expanding its functionality to accommodate broader academic needs.

Discussion and future directions

Interpretation and summary of results

For RQ1, the findings of the first analysis align with research indicating that peer feedback enhances writing quality and critical thinking by helping students identify weaknesses in their drafts (Cho & MacArthur, 2010; Double et al., 2020). As course teaching assistants, we observed that students who received concrete feedback following the given criteria tended to make specific revisions, leading to noticeable improvements. On average, report scores increased by approximately one point across sessions, with most students making at least one meaningful revision based on peer feedback. These results highlight the potential of peer review activities to support learning through collaboration and reflection, though feedback quality remains a key factor (Liang et al., 2025).

Notably, only the first round's mutual evaluation scores had a positive relation on report scores. The lack of improvement in later rounds may indicate diminishing engagement and peer rating reliability over time, underscoring the need to keep participation and feedback quality throughout all course sessions. This trend is particularly relevant in higher education, where students often experience fatigue and heightened workload pressures as end-of-semester exams and deadlines approach (Cano et al., 2024; Dunn et al., 2022). Although we introduced evalution rubrics (Gonsalves, 2024), further peer feedback training (Gorham et al., 2025) may enhance such data-driven design in future implementations. Nevertheless, the findings suggest that even baseline data from individual learning in the first session can support better recommendations, leading to improved review quality.

Although the RQ2 results indicate that three rounds of accumulated peer-help data may not directly contribute to improved performance, potentially due to fatigue or the limited statistical power of small samples, the Sankey diagram illustrates its potential in enhancing engagement with revision work, as students tend to make more rectifications in their reports. These findings reinforce the necessity of sustaining student engagement across multiple tasks, as well as the need for larger samples and extended experimentation to fully assess the system's iterative improvements with more than three rounds. Similar challenges have been reported in studies on data-driven group formation and the reliability of peer evaluation (Liang et al., 2022). Hence, a longer-term study with more participants would allow the system to accumulate additional rounds of peer learning data for recursive learner profiling, providing a more robust validation of the data-driven design.

Regarding RQ3, students who interacted with the visualisation feature were more likely to perceive feedback as higher quality, as they could autonomously select reviewers from the OKLM candidate pool. This finding aligns with research highlighting the role of visualisations in enhancing decision-making and learning outcomes (Brusilovsky, 2024; Schoenherr et al., 2024). By providing transparency into reviewers' proficiency in interconnected paper items, the system enabled more objective and informed selections. This transparency also reinforces the importance of group awareness even before collaboration begins, as knowledge visibility fosters mutual understanding and facilitates deeper discussions later (Schnaubert & Bodemer, 2022). However, potential confounding factors, such as learner diversity, may have influenced this observed effect, which necessitates a rigorous examination in future work to isolate the specific impact of the visualisation feature.

When looking back at the technical gaps, the system integrates recursive data-driven recommendations with autonomous decision-making and anonymised visualisations. This approach achieves a balance between algorithmic guidance and user agency, fostering meaningful knowledge exchange during peer review. The anonymised differential selection of recommended candidates, supported by the OKLM framework, adds dynamism to the ecosystem. The system's effectiveness is validated by performance metrics and positive feedback from pilot users, confirming the viability of the data-driven design principles (Liang et al., 2024).

Theoretical alignment and practical innovations

This study aligns with Vygotsy's (1978) ZPD and scaffolding theories, which emphasise the role of capable peers in advancing learning. Unlike traditional peer learning environments, the proposed system operationalises these theories in a real-world context, requiring an interplay between system design and the broader educational ecosystem (Zhao et al., 2020). Although the study was conducted with a small sample, its university implementation demonstrated how the system can enhance academic rigor by encouraging students to engage critically with their work. Through iterative learner modelling, the system dynamically matches learners with peers who can provide optimal support, addressing a gap in Wright's (2018) book chapter, which primarily focused on static peer assignment strategies that do not adapt to learners' evolving needs.

The recursive recommendation mechanism further builds on the concept of reciprocal teaching, allowing learners to alternate between the roles of asker and helper. This dual-layered learning process reinforces academic knowledge while fostering interpersonal skills such as communication and empathy (Mafarja et al., 2023). Compared to existing systems, this adaptive approach takes a step forward in promoting equitable participation and mutual knowledge construction.

These peer-based learning dynamics are not unique to the Japanese academic reading context. The use of peer review to enhance student-generated artefacts, such as reading reports and communicative tasks, is increasingly adopted across tertiary education worldwide (Double et al., 2020; Gorham et al., 2025). By addressing common challenges such as uneven pairing, lack of transparency in recommendations and limited learner autonomy, our implementation offers transferable insights for broader educational settings globally. Further, policymakers could also support a flipped learning model that leverages data-driven, personalised recommendations to enhance learner autonomy and peer engagement.

Limitations and future directions

This study has several limitations. The small sample size of 31 students and single-institution context limit the generalisability and robustness of findings. Engagement declined over time, possibly due to academic fatigue and the end-of-semester workload (Cano et al., 2024), which may have affected feedback consistency. Merely providing evaluation rubrics appeared insufficient to ensure rating reliability in higher education contexts (Gonsalves, 2024). Although the recursive recommendation system showed early promise, only three rounds of peer review were conducted, making it difficult to fully evaluate long-term effects. For RQ3, potential confounding factors, such as individual learner characteristics, prior knowledge and external learning activities, were not controlled and could influence the perceived quality of feedback. Finally, incorporating motivational elements, such as gamification (L. Li et al., 2024), may help sustain participation over extended use.

Future research should focus on longitudinal studies to evaluate the long-term impacts, integrate AI tools such as large learning models for feedback analysis and explore applications in professional training or informal learning communities (Gao, 2024; Sidhu & Gage, 2021). To enhance the validity of system effects, future work should also employ controlled experimental designs that account for confounding factors and better address learner diversity in terms of digital literacy, prior knowledge, and collaborative experience. Ethical considerations, particularly those related to privacy, transparency and fairness, are essential to ensure alignment with evolving standards for trustworthy artificial intelligence in education.

Author contributions

Author 1: Conceptualisation, Investigation, Formal analysis, Writing – original draft, Writing – review and editing; **Author 2**: System development, Data curation, Pilot analysis, Writing – original draft; **Author 3**: Data curation and pre-procession; **Author 4**: Conceptualisation, Supervision, Writing – review and editing.

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