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Designing LLM-supported informal learning in social reading: a stage-based co-creation approach

Lingling Li

University for the Creative Arts, Canterbury, UK

2410599@students.ucreative.ac.uk

Abstract. This study investigates how large language models (LLMs) can support informal learning in social reading environments. Focusing on critical thinking, collaborative knowledge construction, and group learning, it adopts a stage-based co-design approach grounded in an informal learning cycle. Two participatory design workshops were conducted with social readers, LLM experts, and interaction designers. Participants used first-person narratives and shared tasks to envision LLM-assisted learning processes. Thematic and visual analyses revealed three key design principles: stage-specific intervention, bidirectional prompting, and balancing individual autonomy with collaborative engagement. Building on these findings, we propose a conceptual design model illustrating how LLMs can facilitate social learning in future reading platforms. The study contributes to HCI by expanding the theoretical application of informal learning with LLMs, introducing a novel participatory method, and offering actionable insights for the development of AI-mediated social reading tools.

Keywords: Social reading, Large language models, Informal learning, Working together, Critical thinking, Interaction design

1. Introduction

Reading has long been recognised as a vital activity for acquiring information, expanding knowledge, and developing cognitive and learning skills [1]. Traditionally, it has been framed as a solitary, linear process in which individuals interpret and internalise textual meaning [2]. However, with the rise of digital technologies and widespread internet access, reading practices have increasingly shifted toward more interactive and collaborative forms. The proliferation of e-books and mobile reading devices marked a major shift toward digital engagement [3]. At the same time, platforms like Goodreads and social reading communities like #BookTok have introduced new norms for sharing, discussing, and co-interpreting texts. These changes reflect not only technological innovation but also shifts in cultural practices and learning expectations. Today's readers increasingly seek immediate access to content, peer interaction, and a sense of community, making reading a more collective and participatory experience [4].

Large language models (LLMs) have recently been integrated into digital reading environments to assist with tasks such as comprehension, summarisation, and writing [5]. While these tools enhance access and efficiency, they remain largely optimised for speed and accuracy, offering limited support for exploration, critical thinking, and social learning [6]. As a result, readers often struggle to use LLMs for meaningful reflection, collaboration, or the co-construction of knowledge. This study addresses a central research question: How can we design more effective uses of LLMs in social reading environments to support learning, reflection, and collaboration?

To explore this question, we draw on the concept of informal learning - learning that is interest-driven, contextually embedded, socially situated, and continuously evolving [7]. Unlike formal education, informal learning is flexible, self-directed, and adaptive to individual needs. This framework aligns well with contemporary online reading practices, where users move across platforms, follow their curiosity, and engage with others in nonlinear, interest-driven ways [8]. Yet despite this potential, existing digital reading systems lack concrete design strategies to scaffold critical questioning, sustained reflection, or collaborative learning across the stages of informal learning [9].

To address this gap, we adopted the informal learning cycle proposed by Marsick and Watkins [10] and adapted it into a five-stage model grounded in observed behaviours in social reading. We then applied a creative co-design approach [11] through two participatory workshops involving social readers, LLM experts, and interaction designers. Participants engaged in multi-step speculative design activities, such as first-person scenario building, collaborative feedback, and iterative refinement. Thematic

[12] and visual analyses [13] produced three key design insights: stage-sensitive intervention, bidirectional prompting, and balancing individual autonomy with co-creation.

This study contributes to the HCI community in three ways:

• **Theory**: It demonstrates how informal learning theory can guide the integration of LLMs into social reading, supporting critical thinking, collaboration, and knowledge construction.

• **Method**: It introduces a multi-role, speculative co-design process that fosters deeper engagement and reflection across diverse participant groups.

• **Practice**: It offers actionable guidance for developing LLM-enhanced reading tools that move beyond information retrieval toward dialogic, co-creative learning.

2. Related work

2.1. The potential of LLMs in education and social platforms

Large language models (LLMs) have advanced rapidly in recent years, demonstrating capabilities in natural language processing that have been applied across diverse domains, including healthcare, law, and education [14]. In educational settings, LLMs are widely used to support writing, reading comprehension, and tutoring [15], often providing personalised feedback outside the constraints of formal instruction [16].

Despite this progress, the integration of LLMs into collaborative or social reading environments remains limited and underexplored. Most current systems are designed for individual use, focusing on tasks such as summarisation or direct question answering. These implementations seldom support higher-order cognitive goals such as critical inquiry, sustained reflection, or co-construction of knowledge [17]. LLMs are typically positioned as “answer engines,” rather than as dialogic partners capable of fostering exploratory learning.

Recent research suggests that when aligned with user goals and interaction contexts, LLMs can promote more open-ended, reflective learning experiences. Tools such as Khanmigo [18] and BloombergGPT [19] aim to promote independent thinking by encouraging metacognitive reflection rather than offering immediate solutions. Studies have shown that users working with ChatGPT for idea generation or writing tasks report greater clarity of thought and improved evaluation of sources [20]. In addition, work on AI-supported discourse systems indicates that LLMs can enable collaborative meaning-making through adaptive prompting and dialogue-based scaffolding [21].

However, two key gaps persist in the literature on LLM-mediated social reading:

(1) There is a lack of design frameworks grounded in informal learning theory to guide how LLMs can scaffold thinking and interaction in socially embedded reading contexts.

(2) Existing systems offer limited support for critical reflection, peer engagement, and collaborative knowledge construction - essential components of deeper social learning [22].

2.2. Theoretical background: social reading and informal learning

Reading has traditionally been conceptualised as a solitary, linear activity focused on the internal processing of textual meaning [2]. However, the emergence of digital platforms and networked technologies has transformed reading into a more socially mediated activity. Contemporary readers interact with texts through practices such as annotation, discussion, and sharing, shifting meaning-making from an isolated act to a distributed, participatory process [23]. This shift aligns with key principles of social constructivist learning theory, which emphasises the role of social interaction in knowledge construction [24]. Platforms such as Goodreads and BookTok enable readers to co-create interpretations via comments, hashtags, and shared experiences, embedding individuals within networked communities of meaning [25].

These social reading behaviours also reflect the characteristics of informal learning, which is typically self-initiated, embedded in real-world contexts, and socially situated [7]. Prior research identifies four core dimensions of informal learning: (1) learner autonomy and intrinsic motivation [26]; (2) socio-cultural context and identity [27]; (3) relevance to everyday life [28]; and (4) knowledge development through reflection and experience [29]. Despite the robustness of this literature, few studies have integrated these dimensions into a stage-based framework to explain how informal learning unfolds over time.

Addressing this gap, Marsick and Watkins proposed an informal learning cycle model that includes stages such as recognising a need, exploring solutions, taking action, reflecting on outcomes, and re-integrating knowledge. Though originally developed in the context of workplace learning, the model’s emphasis on situational learning and iterative reflection is well aligned with the nature of social reading, where readers often follow curiosity, engage with peers, and evolve their understanding over time [30].

2.3. Social reading as informal learning

Although traditionally examined within separate research domains, social reading and informal learning share significant conceptual overlap. Social reading offers a real-world, interest-driven context in which individuals navigate content non-linearly and engage in peer-based meaning-making - core attributes of informal learning [7].

Mapping Marsick and Watkins' model onto social reading interactions highlights this alignment. For example, a reader may encounter a provocative post (trigger), explore ideas through annotations or external sources (exploration), comment and discuss with others (social interaction), apply insights in writing or practice (application), and revisit perspectives through reflection (integration). These iterative, socially situated behaviours illustrate how informal learning unfolds in digital reading environments.

This alignment provides both theoretical grounding and design direction for supporting learning in social reading platforms. By treating social reading as a form of informal learning, researchers can more clearly identify where AI interventions, especially LLMs, can support learners not just with answers but by prompting curiosity, critical thinking, and collaborative reflection.

2.4. Structuring LLM-supported social reading through informal learning

To address the identified gaps in how LLMs support learning in social reading, this study adopts a design approach that integrates the informal learning cycle with participatory co-design. Specifically, we draw on the eight-stage Informal and Incidental Learning model proposed by Marsick and Watkins (Figure 1), which conceptualises learning as a context-dependent, recursive process. To better adapt this model for AI-mediated social reading contexts, we merged overlapping steps and reframed them into a five-stage framework: Interest Triggering, Experiencing and Exploring, Social Interaction, Application and Optimisation, and Integration and Internalisation. This revised structure retains the core learning dynamics of the original model while providing a more actionable scaffold for LLM-supported interaction design as shown in Figure 2.

Using this adapted framework, we conducted two structured co-design workshops involving social readers, interaction designers, and LLM experts. Unlike prior studies that primarily rely on platform data or short-term ideation sessions (e.g., [22] and [31]), our method prioritised sustained engagement, reflective iteration, and role-based collaboration. Participants developed speculative first-person design narratives, then refined these through peer feedback and guided revision. The process was informed by speculative design principles [32], encouraging participants to generate imaginative yet grounded proposals. This combination of a theoretically informed learning model and a multi-phase co-design method enabled us to generate user-centred insights and identify actionable strategies for integrating LLMs into collaborative, socially embedded reading practices.

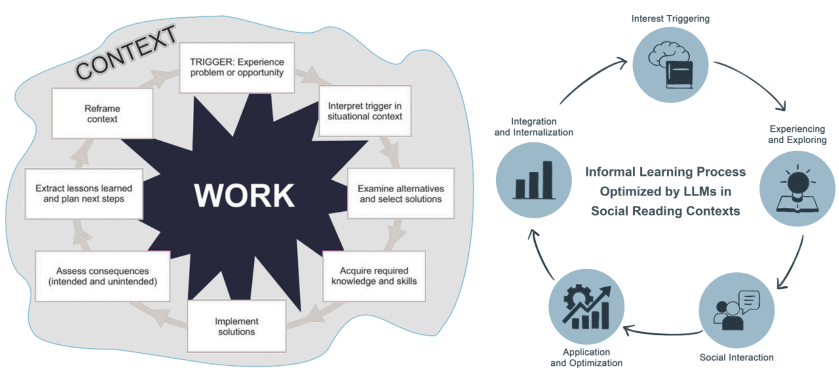

Figure 1. Structure of the marsick & watkins model

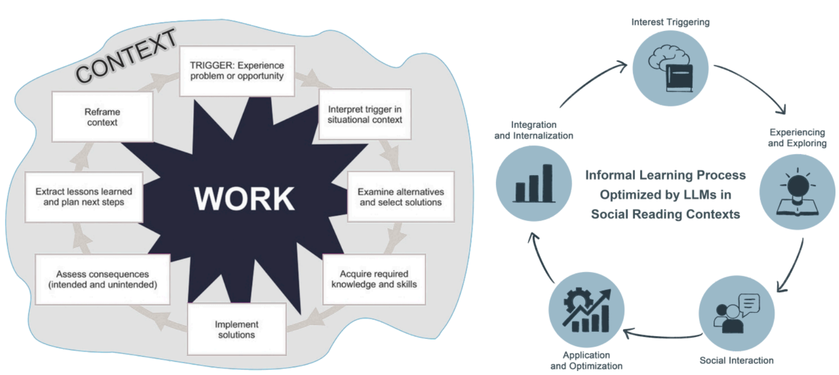

Figure 2. Reconstructed informal learning process model for social reading with LLM support

3. Research setting and methods

3.1. Research design

To explore how LLMs can support informal learning in social reading, this study draws on the informal learning model [10] and aligns it with the behaviour of social reading. A five-stage learning path was designed, and the research was done in two rounds using speculative co-design methods (Figure 3).

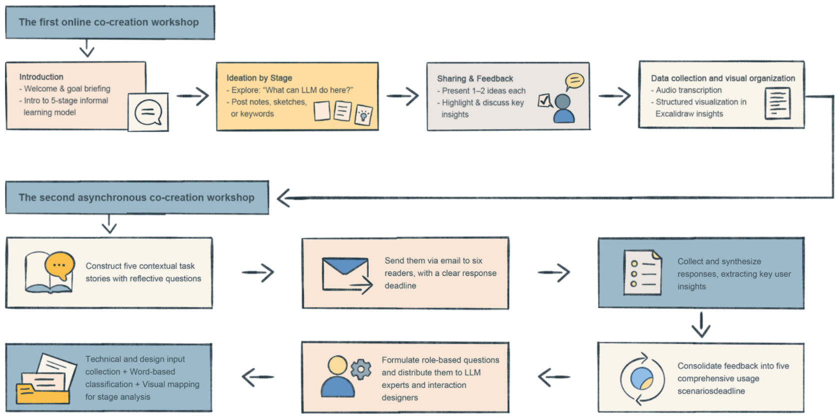

Figure 3. Overall research process

3.2. Participant recruitment

This study used purposive sampling [33] to recruit participants representing three key groups: social reading users, LLM experts, and interaction designers. Recruitment was conducted through social media, tech forums (like Reddit and Hugging Face), and LinkedIn. We used a survey and email follow-up to ensure participants had the right background. In total, 10 people joined the study (6 readers, 2 experts, and 2 designers) as shown in Figure 4.

Initially, we shared the survey widely on platforms like Facebook, Reddit, Instagram, Hugging Face, and Twitter. However, the response rate was low, especially among experts and designers. Later, we posted two open recruitment messages on LinkedIn - one for readers and one for tech workers, which brought in more suitable candidates. We received 64 valid responses (32 readers, 10 designers, 22 LLM workers). We removed people who did not leave contact information or were not interested in the workshop. After reviewing backgrounds and contacting them by email, we confirmed the final 10 participants: 6 active social readers, 2 interaction designers, and 2 LLM/AI professionals.

Each group followed different selection rules. Social reading users needed to: (1) Read on digital platforms more than 5 hours per week; (2) Use platforms like Perlego, Goodreads, Kindle, Douban, WeRead, or Reddit; (3) Participated in at least three reading-related social actions in the past month, such as reviews, comments, or discussions. Responses were verified through the survey and reported platform use.

LLM experts needed: (1) At least 2 years of work with large language models; (2) Familiarity with how generative AI connects with education or reading.

Interaction designers needed: (1) At least 3 years of experience in design, or involvement in multiple user-facing product projects; (2) Experience designing tools for education or reading platforms.

The workshops used Excalidraw (a virtual whiteboard) and Google Meet video calls to allow remote teamwork across time zones. Before the workshop, all participants signed consent forms. During the study, we used ID numbers to keep participants' voices, drawings, and board data private. The research followed the general ethics rules of our university to protect participant rights and data.

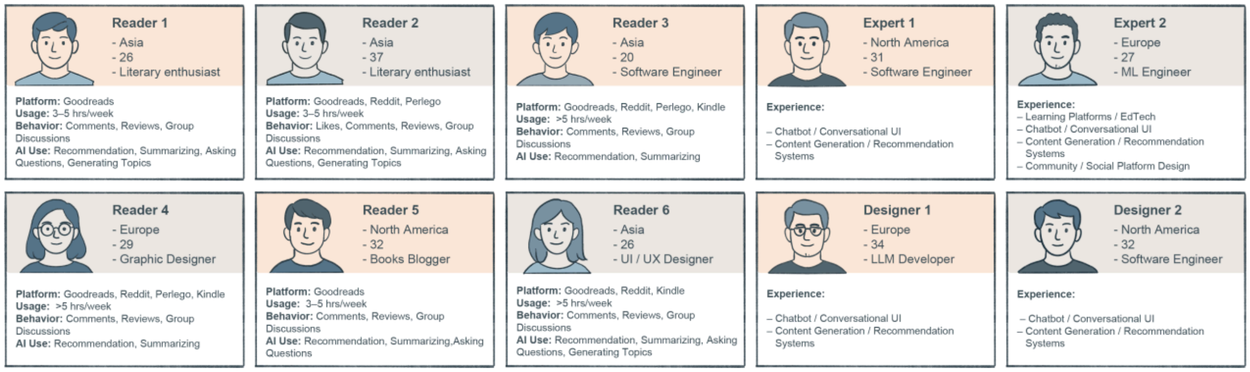

Figure 4. Overview of participant background information

3.3. Workshop process

To investigate how LLMs can support informal learning in social reading, we conducted two structured co-design workshops. First, participants were introduced to a five-stage learning framework adapted from Marsick and Watkins. Second, they generated speculative scenarios to explore LLM roles. Finally, they refined their ideas through collaborative feedback. Further details are presented in the following sections.

3.3.1. Workshop one: preparation and technical setup

To support remote teamwork and guide participants step-by-step, the first round of the workshop was held on Google Meet and lasted around one hour (Figure 5).

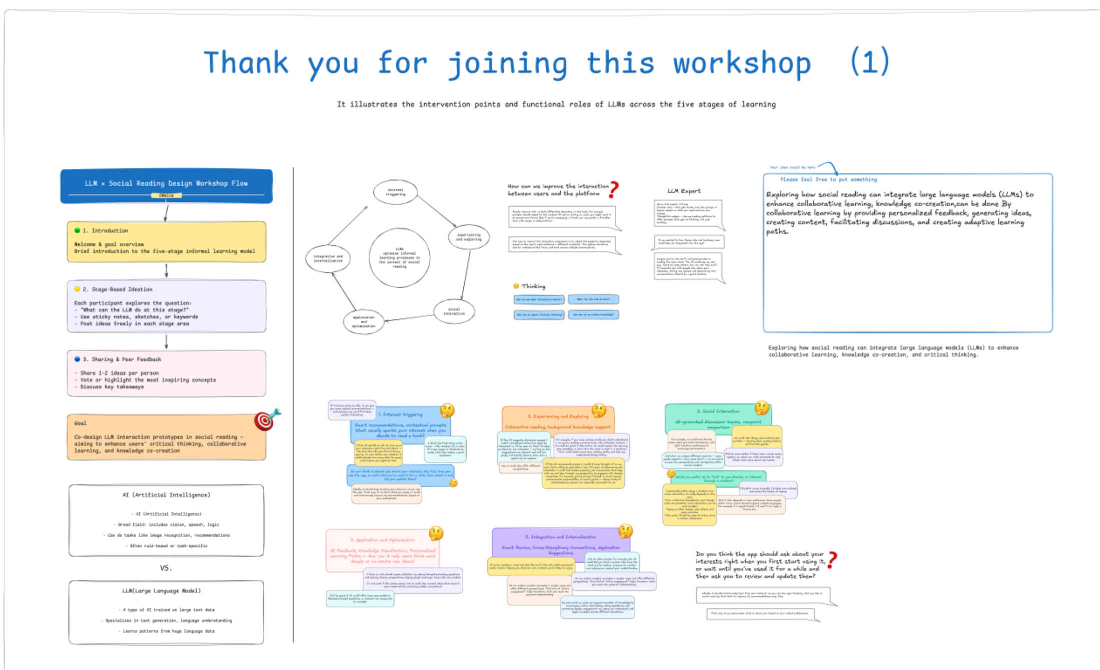

Figure 5. Content of the first workshop

3.3.1.1. Concept introduction and model familiarisation

This part aimed to help participants build a basic understanding of the five-stage informal learning model and connect the theory to their own reading experiences on digital platforms. The researcher provided a brief introduction to the workshop's goals and structure. Then, the five stages - "Interest Triggering," "Experiencing and Exploring," "Social Interaction," "Application and Optimisation," and "Integration and Internalisation" - were explained.

After this overview, participants were guided to reflect on their reading behaviours and common challenges. A short Q&A activity encouraged them to share real examples. For instance, during the ice-breaking session, they were asked to describe a time when they began reading about a new topic. This exercise helped to prompt reflection and build a shared understanding across different roles.

3.3.1.2. Stage-based ideation and individual creation

This stage guided participants to consider how LLMs could assist in each of the five informal learning stages. Before each stage began, the researcher presented guiding questions on the Excalidraw whiteboard to help participants focus on real-world situations. Participants then shared their ideas primarily through typing or speaking, covering use cases or design concepts (Figure 6).

Although the researcher encouraged the use of visual elements such as flow arrows or interface sketches, most participants preferred expressing their ideas through text. This preference was likely influenced by time constraints, the online format, and personal habits. The visual content shown in this section was created later by the researcher based on participants' original ideas to support further analysis.

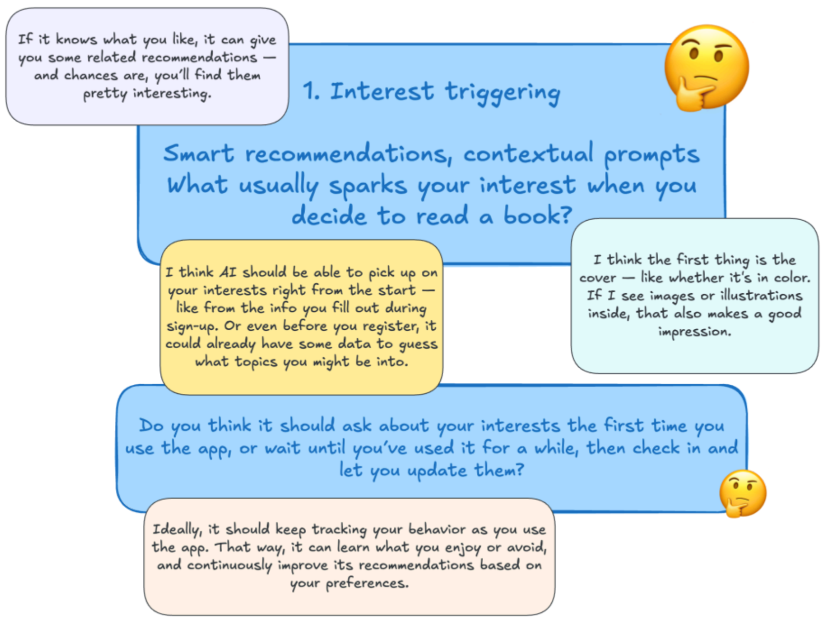

Figure 6. "Interest triggering" stage

E2 (an LLM expert) suggested that LLMs could connect readers who are engaging with the same book and share similar interests, thereby fostering interest-based communities and stimulating initial motivation. She also proposed that LLMs could adapt to individual reading pace and offer thought-provoking prompts to encourage deeper reflection and exploration from the outset.

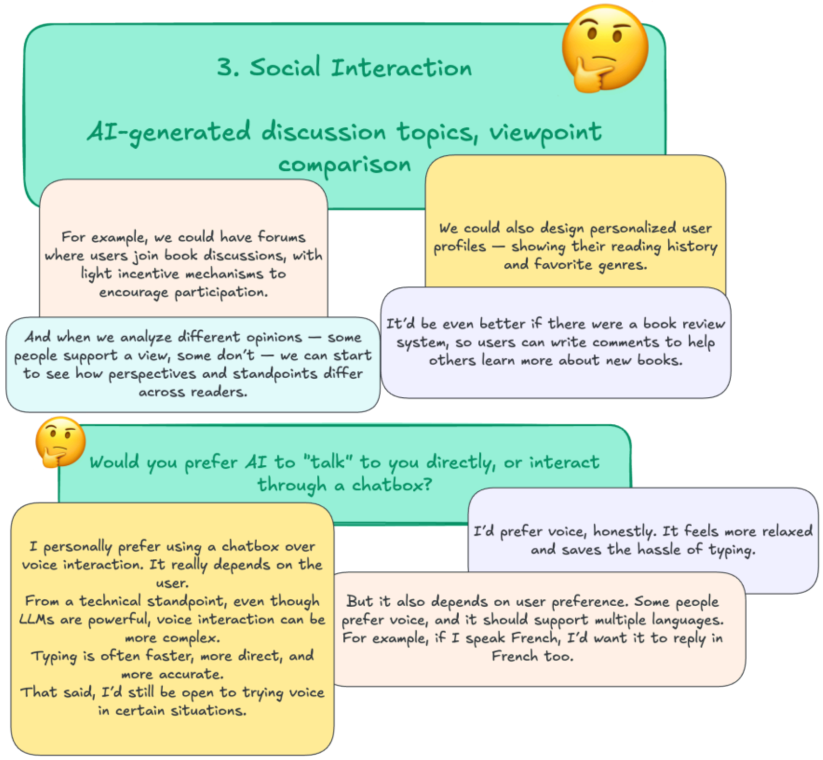

Figure 7. "Social interaction" ideas

In response to the question "How can LLMs improve user interaction?", E1 emphasised the need for adaptable language styles based on task context. D2 proposed tailoring responses to users' input habits to promote more natural engagement. In the Integration and Internalisation stage, participants generally agreed that LLMs should act as thinking partners, supporting reflection and deeper understanding through summary prompts, simplified explanations, and exposure to diverse perspectives. Suggestions also included encouraging note-taking and user-initiated questions to promote knowledge transfer. Overall, the co-creation workshop generated 22 ideas across the five stages (Figure 7).

Data Collection and Organisation

The workshop meeting was recorded and transcribed using the Lecmate tool. After automatic transcription, the researcher reviewed and corrected the text for accuracy. The content was then grouped according to the five stages of the informal learning model. The Excalidraw whiteboard content was organised by the researcher, who selected keywords, logic paths and tags. Analysis employed a method called annotated visual analysis [34] for each stage. The images were saved as PNG files to support further analysis.

Reflection and Deepening Stage

To avoid shallow ideas that sometimes happen in short workshops [35], a one-week reflection and improvement stage was added. Each participant was asked to choose one idea they believed had the most potential, based on the five stages of the informal learning model. They were encouraged to further develop their ideas using pictures and words, or by drawing a user interface or flowchart. Additional detail was requested, including the target user, functional logic, usage scenario, and technical feasibility, in order to build a complete design.

Following this reflection period, a second co-creation workshop was planned. The researcher prepared new design tasks and intended to use a shared whiteboard for further collaboration among readers, experts, and designers, continuing the process for each learning stage. However, due to a sudden technical problem with the platform, all whiteboard content was deleted before the meeting started. As a result, the planned session could not proceed, and the process was halted.

3.3.2. Workshop two: asynchronous co-creation and multi-role analysis

Due to technical issues that led to the loss of whiteboard data, the second planned live session was replaced with an asynchronous co-design task [36]. This change allowed participants to continue reflecting and developing ideas in their own time, while still engaging with the five-stage model.

The goal remained the same: to collect user-generated ideas and analyse them stage by stage to understand how participants perceived the role of LLMs in informal learning, and what types of interactions they preferred. Two complementary methods were used: thematic analysis [12] and annotated portfolio analysis [13], to organise and summarise both text and visual data clearly and consistently. The process had three steps, each with its own data collection and analysis method.

3.3.2.1. Reader tasks and thematic analysis

To prompt deeper thinking, the researcher developed five scenario-based tasks corresponding to each informal learning stage (Figure 8). These were sent via email to six reader participants, who were asked to describe how LLMs could support users and what types of interaction they would prefer. Responses were submitted as Word files and were later structured by participant and stage for ease of analysis.

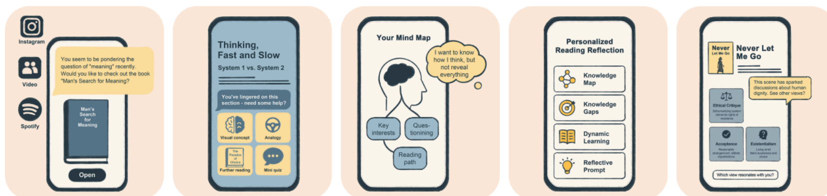

Figure 8. Guided scenario prompts for readers' reflections

Following Braun and Clarke's thematic analysis method [37], the researcher coded the responses line by line to extract design preferences, interaction suggestions, and concerns, particularly around AI guidance, privacy, and user control. Attention was also paid to how user expectations evolved across learning stages.

3.3.2.2. Expert and designer scenario responses and analysis

Based on the feedback from readers, the researcher created five combined scenarios (Figure 9). For each scenario, role-based questions were developed for LLM experts and interaction designers. These questions invited participants to propose ideas for system features, design logic, and interaction strategies. They were sent via email, and the experts were asked to focus on practical, implementable suggestions.

Figure 9. Guided scenario prompts for LLM experts and interaction designers

Data Collection and Organisation

After collecting and organising the responses, the researcher grouped the content based on participant roles - "Expert" and "Designer." The analysis focused on how individuals from different backgrounds understood the same tasks within each learning stage. Particular attention was given to how experts assessed the feasibility of incorporating specific system features, while designers provided suggestions to enhance user experience and interface flow. By comparing the ideas and focus points from different roles, the researcher identified possible areas for cross-disciplinary collaboration. Ultimately, all ideas, preferences, and strategies from both text and images were grouped into main themes and categorised according to the five informal learning stages. These themes revealed user needs at each stage, including preference differences, system design ideas, interaction strategies, and technological limitations. This provided a strong foundation for the subsequent design analysis.

4. Research findings

Based on the five stages of the informal learning model, six readers, two designers, and two LLM experts contributed diverse ideas about how LLMs could help support social reading. Despite their different roles, the participants converged on several key concerns: whether the system fits each stage well, whether the guidance is helpful, whether users can freely ask questions, and how to balance personal expression with collaborative engagement. The main findings below follow the five learning stages.

4.1. Interest triggering

Most reader participants agreed that LLMs could effectively recommend books aligned with users' personal interests. However, several emphasised the importance of data transparency and emotional sensitivity. Participants R2, R3, and R5 expressed concern that systems should clearly communicate how personal data is used, while R4 and R5 cautioned against overly personalised suggestions that infer private emotions or behaviours. Rather than predictive personalisation, readers preferred recommendations that created a sense of emotional resonance. As R6 explained, “If the LLM can connect in the right way at the right time, I will feel more ready to read.”

The interaction designers echoed these concerns, advocating for a “soft and controllable” recommendation system. Designer D1 proposed using emotional keywords to generate a “mood bookshelf,” with recommendations presented in a gentle, empathetic tone. D2 emphasised that the system should prioritise emotional connection over algorithmic tracking and offer users explicit control options, including adjustable filters and visible data labels.

From a technical perspective, the LLM experts provided feasible strategies for emotional alignment. E1 recommended combining emotion recognition with contextual inference to enhance recommendation quality. E2 referenced affective computing methods, including the GoEmotions framework, and emphasised the importance of explainability, adaptability, and user control in emotional modelling.

In summary, participants across roles stressed that LLM-driven recommendations should prioritise emotional attunement rather than behavioural prediction. Effective systems must respect users’ boundaries, avoid overreach, and build trust through transparent, empathetic, and user-controlled design mechanisms.

4.2. Experiencing and exploring

Most reader participants acknowledged that AI could provide valuable support during reading, especially through clarification and explanation. However, they consistently emphasised that such assistance must be non-intrusive and user-initiated. For instance, R1 remarked, “I want LLM to offer a different way of thinking, but I’m afraid if it explains too well, I won’t read the original text.” Similarly, R5 and R6 preferred subtle, optional help, such as “click to show” or lightweight pop-up tips, rather than persistent system-generated messages.

The two interaction designers (D1 and D2) proposed specific UI strategies aligned with this preference for unobtrusive support. Suggestions included edge icons, a “Get Help” button, and a collapsible sidebar containing assistive content designed to preserve the reader’s cognitive flow. D2 also proposed a gentle animation that appears after prolonged inactivity, offering support with the message: “Do you need help?” - mimicking the presence of a friendly peer or study partner.

The LLM experts confirmed that such adaptive support is technically feasible. E1 noted that models can incorporate readability metrics (e.g., Flesch-Kincaid scores) and behavioural signals (e.g., time spent on a section and frequent re-reading) to infer when users are struggling. In such cases, LLMs could provide clarifying examples, simplified explanations, or visual aids. E2 emphasised the importance of context-aware and user-controllable assistance, recommending that support be embedded within the reading interface and adapt to the user’s location and interaction history.

Overall, participants across roles agreed that LLM-based assistance during the Experiencing and Exploring stage should be available on demand, rather than imposed. Readers expressed interest in multi-modal, multi-angle support (e.g., images, examples), but only when it preserves reading rhythm and autonomy. Designers proposed lightweight, minimally disruptive delivery mechanisms. Experts affirmed that current models can already detect comprehension challenges and offer timely, user-sensitive support. These findings indicate strong potential for LLMs to facilitate informal learning, provided they align with user control, pacing, and cognitive flow.

4.3. Social interaction

At this stage, readers expressed significant concerns about the role of LLMs in shaping social interactions and discourse. Several participants were uncomfortable with system-generated opinion grouping or label tagging, fearing that such mechanisms might oversimplify complex thoughts or restrict expressive freedom (R2, R3, R4). As R1 emphasised, “Users should always have the right to ask their questions,” while R6 noted, “LLM’s questions can inspire me, but they should not replace my way of asking.” These responses reflect a strong preference for preserving agency in inquiry and discussion.

Both designers (D1 and D2) shared this scepticism toward rigid classification. Instead, they proposed using flexible idea clusters and user-controllable tagging systems. D1 recommended visual representations, such as overlapping circles, to illustrate conceptual relationships without enforcing strict categories. D2 stressed that system-generated explanations should adopt a suggestive tone, e.g., “You may be close to…” rather than definitive statements like “You belong to…”. Additionally, users should have the option to disable system tagging entirely. These suggestions reflect a design philosophy that values interpretive openness, soft feedback, and user sovereignty.

From a technical perspective, LLM experts proposed feasible alternatives to rigid labelling. E1 suggested using context-aware explanation models, such as SHAP or LIME, to generate probabilistic, natural-language summaries rather than deterministic labels. E2 described how LLMs could leverage multi-dimensional idea mapping and semantic clustering to support user expression without imposing binary categorisations. These techniques - already applied in emotion modelling and social recommendation systems - could be adapted to support shared inquiry and pluralistic interpretation in reading environments.

In summary, participants across all roles emphasised that LLMs should avoid exerting excessive control over social meaning-making. Readers prioritised expressive freedom and questioned ownership. Designers advocated for soft scaffolding tools that preserve interpretive ambiguity and user control. Experts confirmed that technical strategies exist to support these values through open-ended, explainable, and user-adjustable interaction mechanisms.

4.4. Application and optimisation

In the Application and Optimisation stage, readers generally welcomed LLM support for identifying gaps in understanding, particularly through diverse formats such as diagrams, examples, or self-assessment prompts (R2, R3, R5). However, they also articulated clear boundaries regarding system influence. R4, for example, remarked, “I will consider AI’s suggested path, but my interest is more important,” emphasising the importance of maintaining intrinsic motivation. Views on knowledge maps were mixed: while R1, R3, and R5 voiced concern that such structures might constrain open-ended thinking, R4 found them helpful, provided they remained editable and user-driven.

Both designers envisioned non-linear, exploratory knowledge maps as a way to balance structure and user autonomy. D1 proposed a layered node-based interface that reveals deeper content progressively. Features such as “challenge hints” and a “surprise me” button were suggested to prompt critical reflection. Users could annotate maps, draw new connections, and personalise the structure as a thinking space. D2 conceptualised the map as a constellation, allowing users to toggle between “challenge mode” and “reflection mode,” and explore how others’ learning paths intersect with their own. This design encourages multi-directional exploration rather than a linear progression.

LLM experts affirmed that such dynamic learning environments are technically feasible. E1 described how LLMs can incorporate graph-based representations, analogy-driven reasoning, and counterfactual prompts (e.g., “what if” scenarios) to reveal knowledge gaps. Techniques such as presenting opposing viewpoints, comparative framing, and thematic remixing were also recommended to deepen conceptual engagement. E2 added that features like idea networks, quote-based navigation, and cognitive mapping can help users move beyond a single author’s perspective and generate original insights.

Across all roles, participants emphasised that LLM systems should not prescribe a single “correct” learning path. Instead, they should provide adaptive, flexible scaffolds that empower users to pursue personalised inquiry, identify blind spots, and think critically across perspectives. Readers valued multimodal support; designers prioritised open exploration; and experts confirmed that current LLMs can support this vision through structured flexibility and reflective guidance.

4.5. Integration and internalisation

In this final stage, readers were more open to using LLM-generated mind maps or cross-book diagrams, but emphasised that these tools should support, rather than dictate, their thinking. As R2 noted, “LLM’s questions might push me to think more, but it can’t replace my right to explore.” Some participants also drew boundaries around areas LLMs should not touch, such as personal goals, creative ideas, or beliefs (R5, R6).

In response, both designers focused on ensuring that users retain full control over the knowledge map. D1 suggested that the map should allow users to expand layers, change labels, add notes, hide or delete parts, and toggle between “private reading” and “unknown area” modes. The system should also include tools for managing large volumes of content and provide intuitive visual feedback. D2 described the map as a “living diary,” where users could close paths, mark emotions, and keep blank spaces to show that “readers are more than what they click.”

From a technical perspective, LLM experts confirmed the feasibility of these ideas. E1 proposed a “customisable transparency profile” that integrates explainability, user settings, and data minimisation. This approach would allow users to decide how the LLM perceives and presents their information. E2 added that concepts such as “blurred zones” and “non-persistent memory” are already used in emotional AI and privacy systems, and can help build tools that respect user control and deep learning over time.

At this stage, readers were generally willing to use LLM-generated knowledge maps, provided they function as aids for reflection rather than decision-makers (R2, R5, R6). Designers suggested that maps should be user-led and flexible, allowing actions like renaming, deleting paths, or adding emotion tags. These elements should be adjustable, concealable, and personally meaningful. Experts explained that current systems can utilise transparency settings, blurred areas, and memory control to grant users greater control over their data and the learning process. All three groups agreed: the system should not lock users into fixed paths. Instead, it should foster open-ended, flexible environments that support critical thinking and personal meaning-making.

Across the five stages, readers, designers, and experts expressed overlapping views on the ideal role of LLMs in social reading (Table 1). First, LLMs should adapt to each learning stage and individual user needs. Second, their questions and help are more welcome when they allow open responses and spark ideas. Third, in shared spaces, it is important to balance freedom of expression, collaboration, and personal control. These shared views help define the key features of how LLMs should function in social reading and provide a foundation for the next steps in system design.

Table 1. Suggestions from LLM experts and designers

Learning Stages	Expert Insights	Designer Recommendations
Interest Triggering	• Emotion analysis & contextual modeling • Dynamic recommendation algorithm	• Emotional entry points & empathetic language & transparent data interaction
Experiencing and Exploring	• Comprehension barrier detection & auto-triggered visual generation	• Non-intrusive prompts • "Learning companion" metaphor for assistance
Social Interaction	• De-labeled expression • Conceptual spectrum • Resonant phrasing for viewpoints	• Mind maps, fuzzy categorization • Anonymity protection
Application and Optimization	• Contrastive learning mechanisms • Breaking out of opinion echo chambers • Visual path generation	• Constellation maps, "Challenge Me" paths, exploration mode switching
Integration and Internalization	• Fuzzy data zones, non-persistent memory • Privacy control interface	• Reserved blank spaces, self-reflection map management, cognitive sovereignty settings

5. Discussion

This study surfaces several critical tensions and design opportunities in the use of large language models (LLMs) to support learning through social reading. While participants were broadly receptive to system-supported inquiry, they consistently raised concerns regarding timing, agency in question formulation, freedom of expression, and the structure of collaborative engagement. These findings inform a set of design considerations that bridge theoretical, methodological, and practical dimensions.

5.1. Design considerations

We propose three interrelated design mechanisms to guide the development of LLM-supported social reading systems:

1. Stage-Sensitive Intervention

The first mechanism focuses on aligning LLM assistance with the temporal and cognitive dynamics of informal learning. Building on Marsick and Watkins' learning cycle, this design principle emphasises the need for LLMs to adapt their role according to users' evolving needs, ranging from emotional resonance and curiosity stimulation in early stages, to deeper reflection and synthesis in later phases. Participants expressed concern that poorly timed system interventions, such as unsolicited explanations or premature summaries, could disrupt cognitive flow and reduce perceived autonomy. LLMs should therefore function as rhythm-aware companions, capable of detecting cues such as prolonged hesitation, skimming, or affective signals [38], and offering modulated support that users can trigger, ignore, or delay. This principle is also relevant to other domains such as writing assistance, wellness tracking, and creativity support, where pacing and control are central to user experience [39].

2. Bidirectional Prompting

The second mechanism proposes a Bidirectional Prompting Model, which reframes prompting as a co-constructed and interruptible process. While participants appreciated LLM-generated questions that encouraged new perspectives, they resisted systems that monopolised the inquiry space. Such unilateral prompting was perceived as a threat to critical thinking and user agency. To mitigate this, systems should support customisable prompt flows, including prompt-style selectors, editable question templates, and the ability to reject or override system suggestions. This aligns with existing work on learner-driven inquiry [40] and reflective prompting strategies [41], while extending them into LLM-mediated interactions. Recent studies (e.g., [42] and [43]) suggest that prompt fatigue and content alignment can be addressed through adaptive prompt libraries, user intent modelling, and fine-tuned conversational scaffolding.

3. Balancing Individuality and Co-Creation

The third mechanism addresses the tension between personal authorship with collective meaning-making. Social reading platforms often require users to alternate between individual reflection and public dialogue. Participants welcomed features such as idea clustering and visual mapping but rejected rigid categorisation schemes and identity-reducing labels [44]. They called for tools that preserve interpretive ambiguity, enable expressive freedom, and allow asynchronous participation. To support this, LLM-enabled systems should incorporate editable visual artefacts, anonymous contributions, and adjustable levels of co-presence [45]. These affordances allow users to fluidly shift between inward-oriented cognition and outward-facing collaboration, especially during integrative learning phases [46]. Importantly, the system must respect epistemic diversity, allowing multiple interpretations to coexist rather than converging prematurely on singular answers.

5.2. Limitations and future work

This study has several limitations that suggest directions for future research. First, the participant pool - while intentionally diverse in roles (readers, designers and LLM experts) - was limited to ten individuals, constraining the generalisability of findings. Future studies should expand participation to include a broader array of stakeholders, such as educators, platform operators, and policymakers, in order to capture more comprehensive and context-sensitive insights.

Second, the study employed a speculative co-design methodology to elicit forward-looking design proposals. While this approach enabled exploration beyond current system capabilities, it may not fully represent real-world user behaviour or constraints. Subsequent research should incorporate in-situ field studies, longitudinal usage tracking, and prototype-based testing to validate how such design concepts translate into practice.

Third, the study focused exclusively on English-language reading within predominantly Western cultural contexts. As LLM-supported reading practices expand globally, cultural, linguistic, and political variables may significantly shape user expectations and system design. For instance, readers from collectivist cultural backgrounds may interpret co-reading and shared prompts differently than those from individualist cultures. Similarly, multilingual and ideologically pluralistic settings may raise new challenges for prompt framing, personalisation, and data representation.

Finally, this research concentrated on conceptual design rather than technical implementation. While the design mechanisms proposed are theoretically grounded and user-informed, their feasibility, performance, and interaction dynamics remain to be tested. Future work should involve interdisciplinary collaboration with developers and system engineers to create working prototypes and conduct empirical evaluations in real-world reading environments.

In summary, expanding the methodological scope, cultural diversity, and technical realisation of this research is essential for advancing robust, inclusive, and scalable LLM-supported social reading systems.

6. Conclusion

This study explored how large language models (LLMs) can enhance social reading by supporting collaborative learning, knowledge co-creation, and critical thinking. Using a five-stage informal learning model, we conducted two rounds of multi-role co-creation with readers, designers, and LLM experts. Thematic analysis revealed key user needs at each stage, culminating in three design considerations: stage-sensitive support, bidirectional prompting, and balancing individuality with co-creation.

These insights informed a theoretical framework for LLMs in social reading, addressing current limitations such as unclear AI roles and low user agency. By proposing mechanisms like adjustable interaction timing, reflective questioning, and flexible expression, this study offers practical and theoretical contributions toward building more responsive, user-centred AI systems for social learning.

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