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Psychological barriers and learner-centered design of AI-supported online learning

Luyao Shen[1,2,3,*], Kaho Yamaguchi[2], Tsi Yoon Pang[3], Sui-Ting Theh[3], Boon Teck Teng[3], Yosei Miyashita[3,*]

School of Lifelong Education, Nanjing University, Nanjing, China[1]

Yamano Japanese Language School, Tokyo, Japan[2]

Yosei Research Team, Tokyo, Japan[3]

Abstract: Online learning is widely used in higher education, adult education, and professional training, yet many learners struggle to remain engaged, obtain useful feedback, and sustain their participation. Drawing on applied educational psychology, this paper examines how the conditions of online study can create difficulties with self-regulation, attention, social connection, confidence, and the perceived value of learning. It develops a learner-centered conceptual framework that links these difficulties to five areas of AI-supported design: adaptive guidance, assistance with resuming interrupted learning, support for interaction and collaboration, formative feedback, and learning pathways responsive to learners' circumstances. Each area is considered in relation to the psychological process it may support and the risks it may introduce. Particular attention is given to learners' control over their learning, teachers' educational judgment, and the responsible use of learner data. The framework offers a basis for designing and subsequently evaluating AI-supported online learning around learners' experiences and needs.

Keywords: Online learning; Artificial intelligence in education; Applied educational psychology; Self-regulated learning; Learner-centered design.

I. INTRODUCTION

Online courses have become a regular part of higher education, adult education, and vocational training, allowing people to study while working, living far from a campus, or managing other responsibilities. Their use expanded rapidly during the COVID-19 pandemic and has continued through learning management systems, recorded lessons, mobile applications, and AI-assisted tools. This wider availability has prompted closer examination of how digital education is experienced by learners. As UNESCO's 2023 Global Education Monitoring Report observes, the contribution of educational technology depends on its users, its purposes, and the conditions in which it is introduced [1]. These questions remain relevant to decisions about integrating online delivery into ordinary teaching.

For adults combining study with employment or family responsibilities, the freedom to choose when and where to learn can make continued education possible. Online courses also give learners access to materials and instruction that may otherwise be difficult to reach. Yet sustained participation remains a challenge: studies have documented limited interaction, delayed feedback, uneven engagement, and dropout across online learning settings [2,3]. A learner may have access to a complete course and still find it difficult to establish a regular study routine or judge whether the time invested is producing meaningful progress.

Course providers commonly respond by improving the platform, adding activities, revising materials, or encouraging students to manage their time more carefully. Such measures can improve the learning experience, although they leave some difficulties unresolved when learners already have access to adequate resources. In a classroom, the timetable, teachers' presence, informal exchanges with peers, and opportunities to ask questions help learners maintain attention and judge their progress. Online study often requires learners to create much of that structure themselves. The degree of psychological distance from teachers and peers may also increase, especially when communication is asynchronous [4,5]. These changes affect how learners begin tasks, persevere when they encounter difficulties, and return after interruptions.

Research on self-regulated learning links time management, metacognition, effort regulation, and critical thinking with academic performance in online higher education [6]. Studies of social presence have likewise associated a sense of connection with satisfaction and perceived learning [7], while the Community of Inquiry framework explains learning experiences through the interaction of cognitive, social, and teaching presence [4,8]. Evidence concerning adult learners adds the practical pressures of employment, family roles, technical difficulties, and institutional conditions [2,9]. Considered together, these studies help explain why the same online course may be manageable for one learner and difficult to sustain for another, even when both have access to similar content.

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AI applications have expanded the ways in which online courses can respond to individual progress. Learning analytics may help students review their activity, automated feedback can provide responses between teacher consultations, and adaptive guidance can suggest a route through unfamiliar material. A systematic review of AI in higher education documents applications in assessment, prediction, intelligent tutoring, and adaptive systems [10]. Reviews of automated feedback also report promising effects on learning, alongside uncertainty about longer-term outcomes and implications for teachers' work [11]. These capabilities are relevant to learners who need timely guidance but have limited opportunities to seek assistance during a course.

Decisions about what an AI system measures and recommends nevertheless shape the learning experience. A dashboard based on login frequency or task completion may overlook the reasons for interrupted study and the quality of a learner's understanding [12,13]. Frequent recommendations may make study easier to organize while gradually reducing opportunities to select strategies independently [14]. Feedback that gives an answer without explaining an error can also leave learners unsure how to improve. Generative AI adds concerns about accuracy, data protection, transparency, and the responsibilities of teachers. UNESCO's guidance calls for human-centered use, including privacy protection, ethical validation, and pedagogical appropriateness [15]. Educational psychology offers a way to examine these design choices in relation to how learners think, interact, and regulate their work.

Research on online learning has developed substantial explanations of self-regulation, self-efficacy, social presence, cognitive load, feedback, and perceived usefulness [6,7,16,17]. In parallel, research on AI in education has examined a growing range of systems and functions [10,11]. A connection between these bodies of work is especially important at the design stage. For example, before introducing a predictive alert, course designers need to consider which difficulty it is intended to address, whether available data can represent that difficulty, and what a learner or teacher could reasonably do in response. Similar questions arise when selecting adaptive pathways, discussion tools, or feedback systems.

This paper develops a learner-centered conceptual framework for considering those questions. It examines five areas in which online learners may encounter psychological difficulties: maintaining motivation and self-regulation, sustaining attention, forming learning relationships, interpreting feedback and maintaining confidence, and reconciling study with everyday demands and personal goals. It then considers how adaptive guidance, learning-resumption assistance, collaboration support, formative feedback, and context-sensitive pathways might respond to these needs. The proposed links draw on existing educational research and are intended to guide subsequent design and empirical investigation; their effectiveness is contingent on the learning setting and implementation.

The framework brings psychological accounts of online learning into closer contact with decisions about AI-supported course design. It treats difficulties with engagement and persistence as processes that may involve several interacting conditions, including the structure of tasks, the availability of responses from others, and the learner's circumstances. It also sets out the educational purpose of each proposed AI function and considers how that function might affect autonomy, teacher involvement, and data use. These connections are useful when developers and educators must decide which forms of assistance are appropriate for a particular group of learners.

Section II describes the conceptual approach and its psychological foundations. Section III examines the barriers encountered in online learning, and Section IV develops the corresponding design framework. Section V discusses its implications, boundaries, and empirical assessment, followed by the conclusion in Section VI.

II. CONCEPTUAL APPROACH

This study uses conceptual synthesis to examine psychological difficulties experienced in online learning and to develop a framework for AI-supported design. It draws on existing theoretical and empirical work without undertaking a new survey, experiment, or analysis of platform logs. The literature was examined for concepts that help explain learners' participation and persistence and for evidence relevant to possible AI-supported responses. Because the aim is conceptual development, the paper does not claim the exhaustive coverage or formal screening process of a systematic review.

Sources were chosen for their relevance to the framework, with particular attention to established theories, systematic reviews, meta-analyses, and empirical studies of online learning and educational psychology. The synthesis considers how psychological processes affect continued participation, how AI-supported functions might respond, and which educational and ethical conditions shape their use. These questions guide the interpretation of the literature and the development of the proposed design relationships.

Learning difficulties in online courses rarely arise in isolation. Weak self-regulation may be compounded by limited feedback, and poor interaction can make it harder to recover motivation after an interruption. Research on these processes has developed across educational psychology, online learning, and educational technology, often with different practical concerns. Bringing this work together makes it possible to trace a specific difficulty from the learner's experience to a psychological need and then to the design decisions that might address it. The analysis also considers where a proposed intervention could create additional burdens for the learner.

Lewin's person – environment perspective provides the broad basis for this synthesis [18]. Participation in an online course is shaped by learners' characteristics and by the settings in which they study. Task organization, the availability

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of feedback, relationships with peers, home or workplace conditions, and expectations surrounding a course may all affect whether learners continue. Although online provision can increase flexibility, it also transfers some responsibility for organizing and sustaining study to the learner. Examining the interaction between personal circumstances and the learning environment helps place individual difficulties in their practical context.

Several established concepts help explain the different parts of that experience. Self-regulated learning and self-efficacy concern learners' efforts to set goals, monitor progress, and remain confident in their ability to complete tasks. Cognitive load and multimedia learning address the organization of information and the demands placed on attention. Social presence and the Community of Inquiry framework describe how learners experience relationships and interaction in mediated settings. Work on formative feedback and learning analytics examines how information about performance can inform subsequent action. Technology acceptance and adult online learning research add learners' judgments about usefulness, the usability of platforms, and the effects of work and family responsibilities. Their points of overlap help explain difficulties that involve several aspects of the learning experience.

The literature is organized into five areas of psychological barriers: motivation and self-regulation, cognition and attention, social relationships, feedback and self-efficacy, and contextual demands and perceived value. The boundaries between these areas are analytical. Delayed feedback, for instance, can undermine confidence and weaken the motivation to continue, while an interruption caused by work may increase the effort required to resume a difficult task. The categories therefore help identify the source of a learner's difficulty without assuming that it has a single cause.

Each barrier is examined in relation to a learner need and a possible design response. For the AI-related proposals, the analysis considers the support a function could provide, the psychological process through which it might work, and the conditions that could make its use intrusive or ineffective. This keeps the discussion tied to educational purposes when moving from psychological concepts to technological applications.

The synthesis proceeds from the psychological conditions of online study to the needs that arise when those conditions are difficult to manage. It then examines whether AI-supported guidance, assistance after interruptions, interaction support, feedback, or flexible pathways could help meet those needs. Throughout this progression, learners' choice, teachers' judgment, and the handling of personal data remain part of the design question. The resulting relationships are presented as a conceptual proposal for later investigation.

Figure 1 shows how the analysis moves from psychological barriers through learner needs to AI-supported design and its implementation conditions.

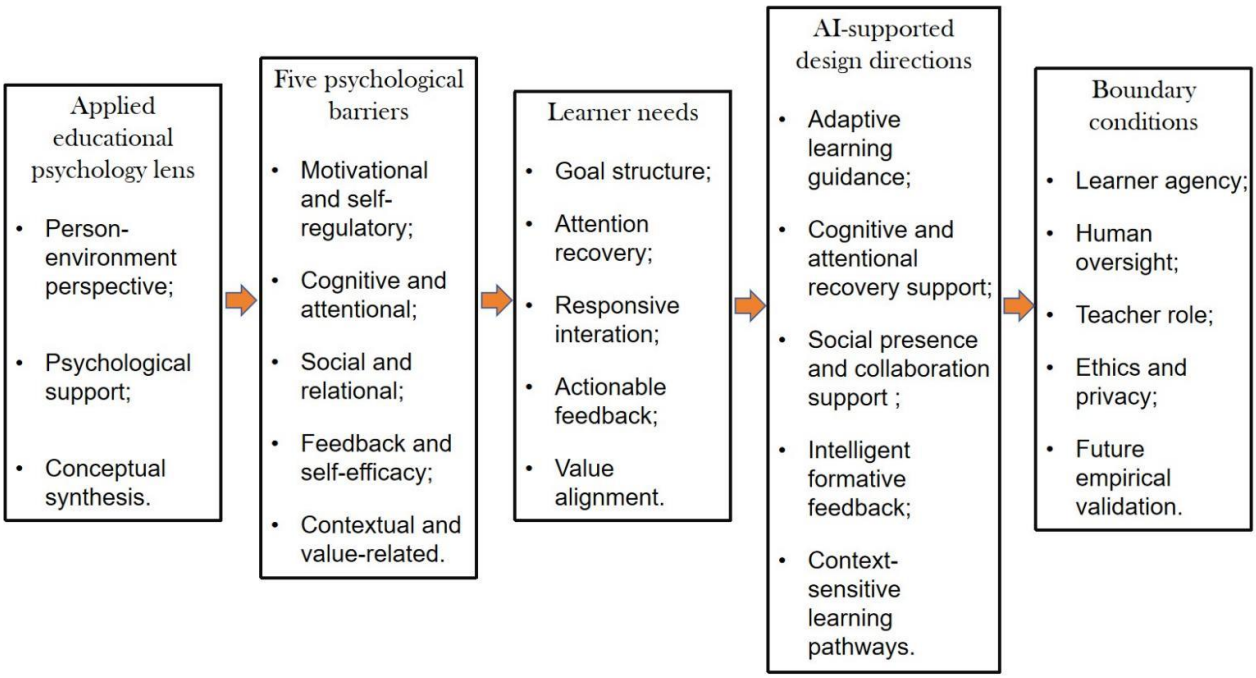


Fig. 1 Analytical pathway of this paper

III. PSYCHOLOGICAL BARRIERS AND LEARNER NEEDS IN ONLINE LEARNING

Online learners may struggle to remain engaged even when a course offers adequate materials and a functioning platform. Their difficulties can develop through changes in the structure of study, the availability of social contact, the continuity of attention, and opportunities to interpret progress. This section examines these experiences through applied educational psychology, with attention to how different difficulties interact over time.

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Research has associated participation and persistence with self-regulation, social and teaching presence, feedback, technology acceptance, and the circumstances in which learners study [3,4,6,7]. In online higher education, time management, metacognition, effort regulation, and critical thinking have been associated with achievement [6]. A sense of social presence is also linked to satisfaction and perceived learning [7,19]. Studies of MOOCs and adult online learning further identify self-efficacy, platform usability, teaching support, employment, and family responsibilities as relevant to continued participation [2,3,20]. These findings provide several perspectives on how engagement may weaken during a course.

Five recurring areas of difficulty emerge from this literature: regulating study, sustaining attention, maintaining learning relationships, using feedback to retain confidence, and fitting learning into everyday life while seeing its value. Their effects may accumulate. Learners who receive little feedback can begin to doubt their progress; limited interaction can make a delayed assignment harder to return to; and repeated interruptions can disrupt a study routine that initially seemed manageable. The discussion below follows these related processes and considers the forms of assistance learners may need.

A. Barriers Related to Motivation and Self-Regulation

In a classroom, scheduled lessons, teacher reminders, and the presence of peers provide a rhythm that helps students continue even during periods of low motivation. The flexibility of online study changes that arrangement. Learners can postpone a recorded lecture or discussion, but they must also decide when to return, how to allocate their time, and whether their progress is adequate. Differences in the ability to organize study can consequently become more visible as learners take greater responsibility for pacing their work.

Self-regulated learning involves setting goals, managing time, selecting strategies, monitoring understanding, and adjusting one's approach when difficulties arise [21,22]. A systematic review of online higher education found relatively consistent positive relationships between performance and time management, metacognition, effort regulation, and critical thinking, whereas evidence for rehearsal, organization, and elaboration was weaker [6]. These distinctions matter because completing course activities provides only a partial view of how learners organize and assess their learning.

Reviews of self-regulation support in distance learning similarly describe the demands that greater autonomy places on planning, monitoring, and reflection [23]. Learners with established study strategies may benefit from choosing their own schedule. Others can gradually fall behind as small postponements accumulate: a lesson missed today is carried into the following week, while unfinished assignments make it harder to decide what to tackle first. The difficulty may emerge well after a learner has enrolled with strong motivation, as delays weaken a sense of progress and control.

Confidence in one's capacity to complete a course can influence how much effort a learner invests when work becomes difficult [24]. Research on MOOCs has associated academic self-efficacy, teaching presence, perceived usefulness, and ease of use with engagement and persistence [3]. A learner who sees a manageable route through unfinished work may be willing to continue, while uncertainty about the next step can make further delays more likely. The role of feedback in shaping this confidence is examined in Section III-D.

Learners dealing with these difficulties may benefit from goals that can be broken into manageable tasks, a clear view of progress, and guidance on how to adjust study strategies. These forms of structure can be particularly relevant to adults studying alongside employment or family responsibilities, whose available time often changes from week to week [2,9]. Course flexibility becomes easier to use when learners can recover a workable plan after falling behind.

B. Barriers Related to Cognition and Attention

Working memory has limited capacity, making the presentation and organization of online material important for sustained attention. Cognitive load theory explains how unnecessary information and complicated interfaces can consume resources needed for learning [25,26]. Principles of multimedia learning, including signaling, segmenting, and removing irrelevant content, address this difficulty by helping learners attend to important information [27,28]. In online courses, learners may also need to decide which of many available materials to prioritize and how separate pieces of information fit together.

The conditions in which online learners study can place additional demands on attention. A lesson watched at home, in an office, or during a commute may be interrupted by messages, household tasks, or other obligations. After attending to an interruption, the learner has to recall the point reached in the lesson and reconstruct the earlier train of thought. Research on task switching and attention residue suggests that such transitions consume mental resources beyond the time taken by the interruption itself [29,30].

Recorded lessons can be replayed, which helps learners recover material they have missed. Frequent replaying can also reflect an effort to reconstruct interrupted thought, even when the learner is already familiar with the material. A learner returning after a phone call might repeat several minutes of a video simply to remember the question being considered. When this occurs repeatedly, the lesson can come to feel disconnected and cognitively demanding, even if the individual explanations are clear. The effort involved in re-entering a task deserves attention alongside the design of the content itself.

Platforms can also create unnecessary cognitive demands when the order of activities is unclear. A course may include discussions, quizzes, and supplementary resources without showing how each relates to its objectives. Learners

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then spend time identifying priorities and interpreting their mistakes before they can decide how to proceed. These decisions can draw attention away from understanding the material, particularly when navigation is complex or relevant information is scattered across several parts of a platform [26,28].

Clear sequencing and a less distracting interface can ease some of these demands, while assistance with resuming a task may help after an unavoidable interruption. Such assistance might preserve the point reached in a lesson, identify the unresolved question, or briefly recall the concepts needed to continue. The design issue extends across the learning process, from entering a task and sustaining attention to returning after a break.

C. Barriers Related to Social Relationships

Learning with others can help students test explanations, ask questions, and remain involved when work becomes difficult. In online courses, the experience of being part of a learning group depends on how interaction is organized and how visible other participants feel. The Community of Inquiry framework describes the contribution of cognitive, social, and teaching presence to meaningful online learning [4,8]. Social presence is especially relevant to whether students experience teachers and peers as real participants with whom they can communicate.

Discussion boards, video meetings, and messaging systems make communication possible, but learners may still feel detached from the people using them. Informal conversations, facial expressions, pauses, and other cues that ordinarily help people interpret responses can be harder to perceive online. This distance may make learners hesitant to ask a basic question or join an unfamiliar discussion, particularly when they cannot anticipate whether anyone will reply [4,5].

A meta-analysis found a strong positive association between social presence and both satisfaction and perceived learning in online education [7]. Research examining online interaction has also reported an indirect relationship with engagement through social presence, alongside links between self-regulation and social presence [19]. These associations help explain why providing opportunities for communication matters, although the experience of responding to and being acknowledged by others remains central to the learner's participation.

Discussion is also relevant to how learners develop understanding. Explaining a position, comparing interpretations, or questioning a peer's reasoning can reveal uncertainties that remain hidden when studying alone. In courses where interaction has little structure, learners may progress through videos, readings, and quizzes with few opportunities for this kind of exchange. Course completion can then provide a limited indication of the cognitive and social engagement involved [4,31].

Silence in an online discussion may reflect uncertainty about whether a question is appropriate, whether it will receive a response, or whether taking part will be worthwhile. In a survey of online engagement strategies, Martin and Bolliger found that students valued regular instructor communication and clearly explained expectations; introductory discussions and collaborative activities were also seen as helpful [31]. Predictable responses and purposeful tasks can make participation feel less uncertain for learners who might otherwise remain on the margins of the group.

Online learners may therefore need accessible opportunities to communicate, reliable responses from instructors, and collaborative tasks with an identifiable purpose. Appropriate peer matching and prompts could help people enter a discussion, provided that participation remains meaningful to those involved. These considerations become important when assessing AI-supported approaches to social interaction in Section IV.

D. Barriers Related to Feedback, Self-Efficacy, and Learning Persistence

Feedback helps learners judge where they stand in relation to a learning goal and decide how to improve. Hattie and Timperley's account of effective feedback emphasizes the goal, current performance, and subsequent action [16]. Research on formative assessment likewise connects feedback with learners' ability to interpret criteria, assess their own work, and regulate subsequent study [32]. These processes can become especially important when learners work independently for extended periods.

Online learners may wait longer for clarification because teachers are less readily available for informal conversations or immediate follow-up questions. A score or a brief indication that an answer is incorrect may confirm that a problem exists while leaving its cause uncertain. This can be particularly difficult in large courses, where instructors have limited time to offer individualized explanations. Learners who cannot identify what went wrong may struggle to choose an effective next step.

Repeated experiences of unclear feedback can also affect confidence. When learners receive a low mark without understanding the reason, they may begin to interpret difficulty as evidence that they lack ability. Feedback that identifies an error, explains what needs attention, and offers a feasible next step creates a different experience of progress [16,24]. For students learning at a distance, such guidance can partly compensate for the immediate reassurance and informal comparisons available in a classroom.

Timely, specific feedback is especially useful when it gives learners a basis for taking action. Diagnostic explanations, opportunities to review an error, and guidance on subsequent practice could help students connect a result with their learning goals. AI-supported feedback is considered in Section IV in relation to this need for understanding and self-regulation.

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E. Barriers Related to Context and Perceived Value

Adults often enter online education because work, family responsibilities, location, or costs make conventional attendance difficult. The same circumstances can continue to interrupt their learning once a course has begun. Caregiving, changing work schedules, financial pressure, and limited study space affect how much time and attention can be devoted to coursework. Learners also make ongoing judgments about whether the benefits of a course justify those demands.

Reviews of adult distance education describe recurring difficulties with time management, competing responsibilities, technical problems, limited interaction, and isolation [2]. A systematic review of adult online learning similarly identifies external conditions, including work and family demands, as influences on engagement and continued participation [9]. Being able to choose a study time is useful, but an unpredictable schedule can leave learning fragmented when there is little help with planning or resuming work.

Experience with digital platforms adds another source of variation. A learner accustomed to online services may have little trouble submitting work or joining discussions, while an unfamiliar login procedure or assignment interface may discourage a newcomer early in a course. Davis's technology acceptance model identifies perceived usefulness and perceived ease of use as influences on technology acceptance [17]. In online learning, unnecessary technical effort can weaken the connection learners see between using the platform and achieving their educational goals.

The value learners attach to a course can shape their willingness to continue when other obligations intervene. Research on MOOCs has associated perceived usefulness with engagement and perceived ease of use with persistence [3]. Adults preparing for a qualification, for example, may want to understand how an exercise relates to examination requirements, while people pursuing career development may look for practical applications. When that connection remains unclear, completing the minimum required activities may seem more reasonable than devoting further effort to the material.

Learning arrangements can respond to these circumstances through manageable schedules, accessible technical assistance, and clear connections between tasks and personal goals. Learners may also benefit from feedback that shows what they have gained and where their new skills can be applied. Because the pressures of work and family may change throughout a course, a usable pathway must allow students to resume progress after periods of limited participation.

F. From Psychological Barriers to Learner Needs

Across these areas, the demands of online learning extend from organizing individual tasks to maintaining relationships and judging the value of continued study. Learners may need to plan without a fixed classroom timetable, recover attention after interruptions, seek responses from others, and interpret feedback on their own. The same freedom that enables some people to study effectively can become difficult to manage when several of these demands arise together.

The framework groups the corresponding needs around manageable goals and visible progress; clear materials and assistance after interruptions; responsive interaction with teachers and peers; feedback that makes improvement possible; and learning arrangements that reflect personal circumstances. These needs overlap in practice. A timely response from an instructor, for example, may clarify a task and restore confidence, while a workable study schedule may reduce both attentional disruption and uncertainty about progress.

Table 1 sets out the five areas of psychological barriers, examples of how they appear during online study, and the learner needs associated with each area.

Table 1. Major psychological barriers in online learning and corresponding learner needs

Barrier category	Core psychological issue	Typical manifestations	Corresponding learner needs	Representative literature
Motivational and self-regulatory barriers	Goal setting, time management, progress monitoring, effort regulation, and perceived control	Procrastination, unstable engagement, delayed task completion, and loss of control	Clear goals, visible progress, staged prompts, and learning-strategy support	[6,21–23]
Cognitive and attentional barriers	Cognitive load, distraction, interruption, and task resumption	Fragmented learning, repeated reviewing, and difficulty re-entering learning tasks	Structured content, a low-distraction interface, and task-resumption support	[25,27–30]

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Social and relational barriers	Reduced social presence, psychological distance, and weak collaboration	Hesitation to participate, weak belonging, limited peer interaction, and shallow discussion	Responsive interaction spaces, stable peer connections, and visible instructor support	[4,7,19,31]
Feedback- and self-efficacy-related barriers	Delayed or unclear feedback and uncertainty about current performance and next steps	Low confidence, difficulty identifying errors, and reduced persistence	Timely, specific, and actionable formative feedback	[16,24,32]
Contextual and value-related barriers	Work and family pressures, digital barriers, and weak perceived usefulness	Discontinuous learning, minimal engagement, and reduced commitment	Flexible but structured pathways, low-threshold technical support, and stronger connections between learning and personal goals	[2,3,9,17]

The needs identified here guide the design proposals developed in Section IV, where the potential contribution and limitations of different AI-supported functions are considered in relation to actual learning activities.

IV. A LEARNER-CENTERED FRAMEWORK FOR AI-SUPPORTED ONLINE LEARNING DESIGN

The psychological difficulties examined in Section III point to several opportunities for assistance within online learning systems. Learners may need help setting priorities, returning to unfinished work, obtaining responses from others, understanding errors, or fitting study into changing routines. The framework developed here connects those needs with AI-supported functions while considering the conditions in which their use could be helpful. The emphasis throughout is on the experience of learning and the decisions learners and teachers need to make during a course.

AI applications in education already include tutoring, adaptive pathways, automated feedback, learning analytics, and predictions intended to inform instructional decisions [10,33]. Meta-analyses have found benefits from intelligent tutoring systems in some settings, with outcomes varying according to the subject, instructional design, teacher involvement, and characteristics of learners [34–36]. Learning analytics dashboards and reminders also offer ways to monitor progress, although reviews have questioned how consistently these tools draw on theories of self-regulation or help learners select strategies [12,13,37]. Such evidence makes the purpose and interpretation of an intervention as important to design decisions as its technical capabilities.

The proposed framework considers five areas of AI-supported design. Adaptive guidance may help learners organize their work; resumption assistance may reduce the effort of returning after interruptions; interaction support may make responses and collaboration more accessible; formative feedback may clarify how to improve; and context-sensitive pathways may help learners connect study with their circumstances and goals. Each proposal arises from a psychological need discussed in Section III, and the boundaries between the areas remain flexible because learners often experience several difficulties at once.

These proposals are conceptual inferences grounded in educational psychology and research on AI in education. Their effects will depend on the course, the learner group, and the way the functions are introduced. Table 2 relates the design areas to their intended psychological contributions, illustrative functions, and possible risks, providing a basis for considering which approaches merit empirical testing.

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Table 2. Mapping learner needs to AI-supported design directions

AI-supported design direction	Target learner need	Illustrative support functions	Intended psychological contribution	Key risks and boundary conditions	Representative literature
Adaptive learning guidance	Self-regulation support	Progress prompts, pathway suggestions, strategy cues, and progress visualization	Greater goal clarity, perceived control, progress monitoring, and strategy adjustment	Over-monitoring, reduced autonomy, and reliance on shallow behavioral metrics	[12,14,37,38]
Cognitive and attentional recovery support	Attention recovery and task resumption	Resumption cues, micro-reviews, task-continuation support, and segmented learning options	Lower task re-entry costs, reduced extraneous cognitive load, and improved learning continuity	Excessive notifications, fragmented pacing, and intrusive intervention	[26,28,30]
Social presence and collaboration support	Responsive interaction, belonging, and peer connection	Peer matching, discussion prompts, discussion summarization, participation reminders, and teacher alerts	Stronger social presence, belonging, participation, and collaborative engagement	Formulaic interaction, algorithmic grouping bias, and displacement of meaningful human response	[7,8,19,31]
Intelligent formative feedback	Actionable feedback and confidence support	Diagnostic feedback, graduated hints, targeted practice, and progress-linked feedback	Improved self-efficacy, clearer performance interpretation, and more actionable next steps	Inaccurate or opaque feedback, excessive guidance, and learner overdependence	[11,16,32]
Context-sensitive learning pathways	Flexibility, value alignment, and continuity	Time-sensitive task recommendations, goal-based content emphasis, flexible task length, and progress portfolios	Stronger perceived usefulness, learning continuity, and persistence	Privacy risks, profiling bias, limited transparency, and unequal access to support	[3,15,17,39]

A. Adaptive Learning Guidance and Support for Self-Regulation

Without a fixed classroom schedule, online learners must often decide which tasks deserve attention and how to recover when their plans are disrupted. An adaptive guidance system could use stated learning goals, completed assignments, and demonstrated understanding to help learners identify manageable next steps. Someone who has fallen behind might receive a prompt to prioritize a prerequisite activity, while a student repeatedly struggling with a concept could be offered a relevant review. Learners who have mastered basic material might instead be invited to attempt more demanding work. Recommendations based on time spent online would require particular care because study duration alone says little about understanding.

Self-regulated learning research emphasizes setting goals, monitoring progress, and revising strategies as learning develops [21,22]. AI-supported guidance may make these processes easier by bringing together information that would otherwise remain scattered across a course. A review of learning analytics interventions describes efforts to identify

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learners' regulatory states and offer assistance at different stages of study [38]. Whether an intervention is useful depends on how readily learners can understand the recommendation and decide what to do with it.

The quality of this guidance depends in part on what the system treats as evidence. Completion rates, logins, and clicks can describe activity but give an incomplete picture of motivation or comprehension. A learner may study effectively offline, while another may spend considerable time on a platform without resolving a difficulty. Reviews of learning analytics dashboards have found that many tools display information without adequately explaining how it should inform metacognition or strategy choice [12,37]. Recommendations therefore need to be connected to learning objectives and interpretable evidence, with room for teachers and students to question what the data appear to show.

One practical option is to present several reasonable next steps with a brief explanation of why each might help. After repeated errors on a concept, for example, the system might suggest a short review, offer practice questions, and leave the learner free to continue with the next unit. A recommendation of this kind gives the student information for planning while preserving the opportunity to make and evaluate an independent decision. The balance is relevant to concerns that highly automated guidance may weaken learner agency over time [14].

B. Support for Cognitive and Attentional Recovery

An interruption during online study can leave learners unsure where they stopped and what they intended to do next. Someone returning to a lesson after a work call may need to reconstruct a line of reasoning before continuing. Research on disruptions to computing tasks and attention residue indicates that switching tasks can make this return cognitively demanding [29,30]. The frequency of such interruptions makes recovery a practical design concern for learners who study around other obligations.

AI systems could help by preserving the point reached in a task and briefly identifying its unresolved elements. On returning, a learner might see the last concept covered, the question being attempted, and an option to review the preceding explanation. After a longer absence, a short recap or small preparatory activity could provide an easier way back into the course. Where interruptions repeatedly occur during lengthy activities, the system might suggest a more manageable division of work. These functions would need to draw on the learner's actual study record and remain optional.

Cognitive load theory provides a rationale for minimizing the effort required to find one's place again, while multimedia learning research emphasizes clear structure and cues that direct attention to relevant information [26 – 28]. In this setting, an effective reminder would be brief enough to restore the context of a task without introducing substantial new material. The assistance is aimed at preserving resources for understanding and applying what the learner has already begun to study.

Recovery tools can themselves become distracting when reminders arrive too often or when every lesson is divided into numerous prompts. Their timing and frequency matter as much as the information they provide. A student already engaged in sustained work may prefer no intervention, while someone returning after several days may welcome a clear starting point. Giving learners control over prompts and allowing the system to remain quiet during uninterrupted study would respond to these different situations [14,28].

Adult learners frequently move between employment, family duties, and coursework, making a fixed schedule difficult to maintain [2,9]. For them, a record of unfinished work and an accessible route back into a lesson may be particularly valuable. Such assistance could preserve continuity across short and irregular study sessions without imposing a faster pace than the learner can sustain.

C. Support for Social Presence and Collaboration

When an online discussion receives little response, learners may hesitate to contribute again even if the platform offers several ways to communicate. The Community of Inquiry framework places social and teaching presence alongside cognitive presence in accounts of meaningful online learning [4,8], and research has linked social presence with satisfaction, perceived learning, and engagement [7,19]. AI-supported interaction tools should therefore be considered in terms of whether they help learners reach other people and participate in a responsive learning group.

A system could suggest suitable partners for a collaborative task by considering learners' interests, goals, and progress. During discussion, it might offer an open question when conversation has stalled, organize existing contributions so newcomers can follow them, or bring an unanswered question to the instructor's attention. These uses are plausible ways to reduce the effort involved in finding collaborators or entering a discussion. Research on online engagement indicates that interaction with instructors, peers, and content benefits from deliberate course design [31]; the AI functions proposed here would operate within that broader structure.

A learner's reluctance to post may reflect concern that a question is too basic or uncertainty about whether a reply will come. A well-organized discussion space with clear expectations can reduce some of that hesitation. Martin and Bolliger's findings suggest that students value instructor communication and structured opportunities for collaboration [31]. AI-generated summaries or prompts may help participants navigate the space, but their usefulness depends on whether the resulting exchange becomes meaningful to the learners themselves.

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Trust within a learning group develops through responses from teachers and peers. If most visible replies come from an automated system, students may obtain quick information while continuing to feel detached from the group. AI can assist with organization and alert people when a response is needed, leaving judgments about a learner's concerns, encouragement, and complex educational feedback with the teacher and the learning community [10,14]. This division also gives learners a clearer understanding of whom they are communicating with.

A course might use automated prompts to bring unattended questions to a tutor, assist with finding collaborators, or summarize a discussion that has grown difficult to follow. Teachers would continue to shape the tone of exchanges and decide when direct involvement is needed. The extent of AI involvement should be judged against the quality of relationships and discussion that develop, since more frequent automated interaction does not necessarily mean that learners feel better connected.

D. Formative Feedback and Support for Self-Efficacy

In online courses, a learner who receives only a numerical score may have difficulty identifying the source of an error. Feedback research describes the importance of knowing the intended goal, the current level of performance, and the action needed to improve [16]. Formative assessment also helps learners interpret standards and develop greater control over their subsequent work [32]. These functions are especially relevant when students are studying at a distance and cannot readily ask an instructor to clarify a confusing result.

AI-supported feedback could identify recurring errors in a set of answers and recommend an explanation or exercise related to the underlying concept. A system might initially offer a small hint and provide more explicit guidance if the learner remains uncertain. Linking feedback on an individual activity to earlier work could also help students recognize progress over time. A review of automated feedback in online learning describes its potential to scaffold understanding and connect performance with learning objectives [11]. The educational usefulness of any particular response would still depend on its accuracy and on whether the learner can act on it.

The evidence for automated feedback is promising but uneven. A systematic review reports learning benefits in a number of studies, while finding limited evidence about sustained effects across subjects and reductions in teacher workload [11]. In practice, recurring errors on routine tasks may be suitable for immediate automated explanation, whereas ambiguous reasoning or persistent frustration may require direct teacher involvement. Combining these responses allows the system to address delays in feedback while retaining opportunities for more considered educational judgments.

Feedback can also influence whether learners believe they are capable of improving. Repeated marks without explanation may leave a student unsure how to proceed, whereas identifying a specific problem and an achievable next step can help restore a sense of control [16,24]. This distinction matters for students who have few opportunities to compare their interpretation with that of a teacher or classmate. An effective response should help them understand both the error and what they can try next.

The level of assistance needs to be adjustable. Detailed hints offered too early may reduce opportunities for independent thought, while an unexplained recommendation may be difficult to trust. One option is to ask learners to reconsider the relationship between their answer and the target concept before displaying a more specific explanation. Providing a reason for the feedback and allowing learners to request additional help can make guidance more transparent and compatible with self-regulation [11,32].

E. Context-Sensitive Learning Pathways and Support for Perceived Value

Online learners often have to arrange study around paid work, family responsibilities, or unpredictable changes in their daily routines. A pathway designed for long, uninterrupted sessions may become difficult to follow even when the learner is committed to completing the course. Context-sensitive support would take available study time and personal goals into account while keeping the required learning objectives clear.

A platform might offer a short concept review when a learner has ten minutes available and suggest a longer problem-solving activity when a more substantial block of time is possible. It could also give greater prominence to the applications relevant to the student's aims: practical tasks for vocational learners, for example, or assessment requirements for those working toward a qualification. Progress records could connect completed activities with the skills or goals learners hope to achieve. Reviews of adult online education identify time pressures, family obligations, and technical difficulties as continuing influences on participation [2,9], making this flexibility relevant to the organization of coursework.

Technology acceptance research suggests that perceived usefulness and ease of use influence people's willingness to adopt a system [17]. Research on MOOCs has likewise associated usefulness with engagement and ease of use with persistence [3]. A personalized route through a course may consequently have limited appeal if learners find the platform difficult to navigate or cannot understand why a recommended activity matters to their goals. Clear explanations and manageable tasks are therefore important parts of the experience.

Learners may judge the value of study partly through evidence of what they can now understand or do. A portfolio of completed work, feedback linked to competencies, or an example connecting a lesson with a workplace task can make progress easier to recognize. Such information can be useful when the benefits of a course are gradual and learners are

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deciding whether to continue allocating scarce time to it. Connections between learning activities and practical goals are consistent with evidence concerning perceived usefulness [3,17].

Personalization may require information about schedules, performance, preferences, and study behavior, which creates responsibilities for those collecting and using it. UNESCO's guidance calls for attention to privacy, ethical assessment, and educational suitability [15]. Research on human-centered learning analytics also describes the risk of mistrust when learners and teachers are excluded from design decisions [39]. Data should therefore be limited to what an intervention needs, collected transparently, and used in ways that learners can understand and influence.

F. Conditions for Human-Centered Implementation

The framework relies on several conditions that cut across the individual design proposals. Activity records provide clues about participation, although login counts and completion rates offer an incomplete picture of learning and motivation [12,13]. Teachers remain important when interpreting uncertain information, responding to personal concerns, and shaping the relationships through which students learn [4,10]. Learners also need opportunities to question recommendations and choose their own strategies, particularly where repeated automated guidance may encourage dependence [14,39]. Across these activities, responsible data practices require clear explanations of what information is collected, how it informs recommendations, and how potential bias or privacy risks are addressed [15,39].

In practice, responsibility would be shared: AI could provide accessible reminders, explanations, and other routine assistance, while learners would retain control over their choices and teachers would interpret information in the broader educational context [14,15]. This arrangement provides the basis for considering the framework's implications and limitations in the discussion that follows.

Figure 2 brings together the five areas of psychological barriers, the corresponding AI-supported design proposals, and the conditions for their use, with the learner at the center.

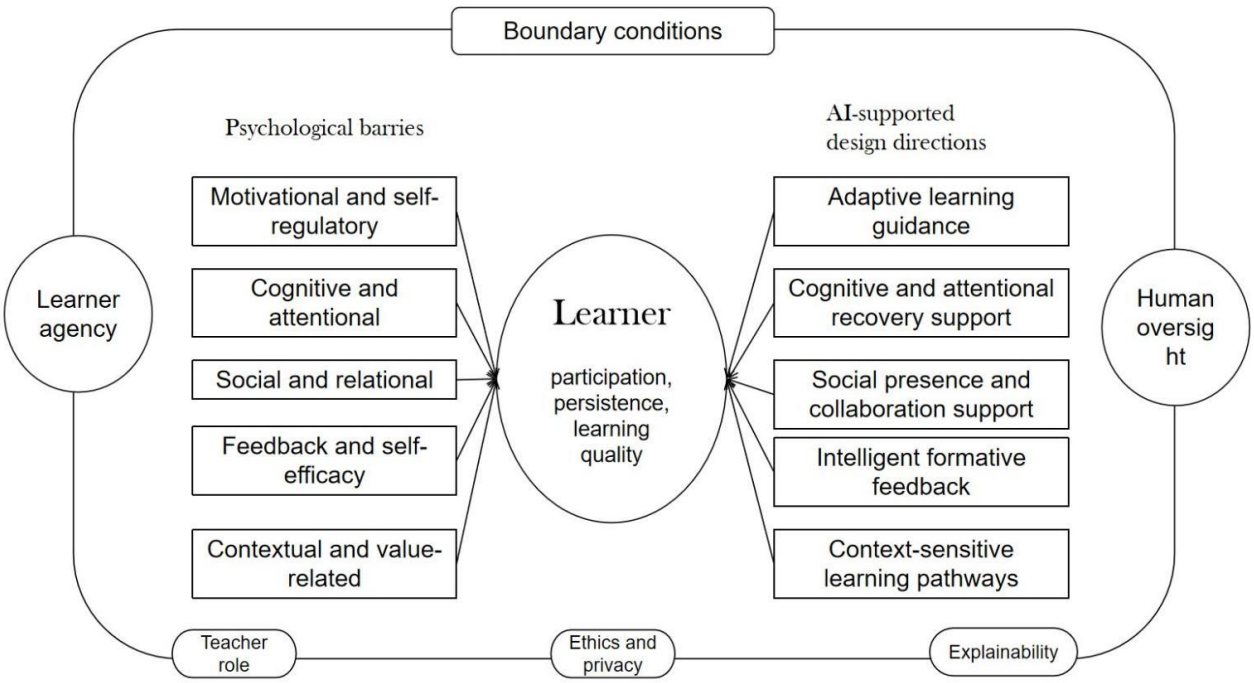


Fig. 2 Learner-centered framework for AI-supported online learning design

V. DISCUSSION

The framework links familiar psychological difficulties in online learning to possible uses of AI, but its value depends on how those connections are understood and assessed. For course designers, this raises questions about the kinds of assistance students need, the evidence used to identify those needs, and the division of responsibility between systems, teachers, and learners. The following discussion examines these issues in relation to existing educational research and considers how the proposed relationships might be tested.

A. Reframing Online Learning Design as a Psychological Support System

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A learner's difficulty in completing an online course may develop through several related experiences. An unclear study plan can make it harder to start an assignment; limited responses from others may leave questions unresolved; and repeated interruptions may weaken confidence that progress is possible. These experiences point to the importance of examining how a course sustains learning over time. Platform stability and access to resources remain necessary, while the organization of tasks, opportunities for interaction, and quality of feedback shape how learners use those resources.

Research on self-regulated learning connects time management, metacognition, and effort regulation with achievement [6,23]. Work on social presence associates a sense of connection with satisfaction, perceived learning, and engagement [4,7,19], while feedback research shows how understanding current performance can help learners decide what to do next [16,32]. Although these bodies of literature focus on different processes, they converge in situations where learners must study with limited immediate support. The present framework uses their combined insights to examine how task organization, attention, interaction, and feedback operate within the same learning experience.

Consider a student who stops participating after several missed lessons. A weak sense of direction may be part of the problem, but the learner could also be unsure about earlier material, reluctant to seek help, or unable to find a suitable time to resume. Responding solely with another reminder might therefore have little effect. Examining these possibilities together gives educators a more useful starting point for deciding whether the course needs clearer guidance, a way to recover unfinished work, or more direct human support.

B. From an AI Function-Oriented Approach to a Learner Needs-Oriented Approach

Research on AI in education has examined a wide range of applications, including tutoring, automated feedback, analytics, prediction, and recommendation. A systematic review of higher education research found substantial attention to system development and prediction, alongside comparatively limited involvement from educators and pedagogical perspectives [10]. The availability of these technologies creates opportunities for online courses, but it also makes the selection of appropriate functions a significant educational decision. A prediction of low participation, for example, is useful only when educators understand the difficulty it may represent and have an appropriate response available.

Linking a proposed AI function to a particular learner need makes both design and evaluation more specific. A reminder intended to help students resume study should be assessed for whether it makes returning to a task easier. A discussion prompt aimed at improving social presence calls for evidence about participants' experiences of interaction. Feedback intended to strengthen confidence requires attention to whether learners understand their errors and can plan subsequent work. These purposes provide more informative criteria than the number of features a platform offers.

Learning analytics dashboards illustrate the importance of this link. Reviews have found that dashboards frequently present information intended to support self-regulated learning, while their theoretical connections to learners' actual strategy use remain insufficiently explained [12]. A progress bar or risk label can draw attention to an issue, yet students still need to know how to interpret the information and which adjustment might be useful. Design and evaluation should follow what learners do with the information after seeing it, including whether it helps them reflect on their study practices.

Automated feedback raises similar questions. Studies reviewed in the literature have reported improvements in learning performance, although longer-term effects, workload implications, and support for higher-order learning remain less well established [11]. Faster responses are valuable when they clarify an error or enable a student to continue with a task. Their educational contribution is less clear when feedback is generic or difficult to interpret. Examining how learners revise their work after receiving a response would help assess these differences.

C. Human–AI Collaboration and the Role of Teachers

AI systems can process learning records and deliver prompt responses, while teachers are often needed to interpret what those records mean for an individual student. A missed assignment may reflect misunderstanding, competing responsibilities, or difficulty navigating the course; the appropriate response may vary accordingly. Teachers can ask follow-up questions, recognize frustration, and adjust expectations in ways that draw on knowledge of the student and the class. Decisions of this kind are central to how AI assistance might be integrated into teaching.

Molenaar's account of hybrid human‑AI learning technologies provides a useful perspective, emphasizing augmentation and collaboration between human and artificial intelligence [14]. Within the proposed framework, AI could assist with routine guidance and the timely presentation of relevant information, leaving teachers responsible for interpreting complex difficulties and sustaining educational relationships. The particular division of work would depend on the course and on the capacity of teachers to review and respond to system outputs.

Information provided to teachers also needs to be interpretable. A warning that a learner has been absent for several days offers little guidance unless the teacher can examine the observations behind it and consider alternative explanations. Changes in work or family responsibilities may be more relevant than declining motivation; repeated difficulty with particular material may call for another kind of response. Allowing educators to review these circumstances reduces the risk of treating a behavioral indicator as a complete account of a student's learning.

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Learners should have similar opportunities to interpret and adjust the assistance they receive. Personalized reminders and recommended pathways can be useful when study becomes difficult to organize, but habitual reliance on the system may narrow the choices learners make independently. Asking students to review suggested options, explain their preferred next step, or adjust reminder settings could allow assistance to contribute to the development of self-regulation. The aim is for learners to become more capable of managing their work as their experience grows.

D. Ethical Boundaries, Trust, and Sustainable Use

Personalized assistance relies on information that may reveal patterns in a learner's daily life, including study times, progress, interactions, and periods of absence. These records can inform recommendations, but their collection also creates risks of intrusive monitoring, inappropriate labels, privacy breaches, and biased judgments. Such concerns become more substantial when a system combines activity data with inferred personal characteristics or makes decisions that learners cannot readily question.

A systematic review of human-centered learning analytics and AI in education found growing attention to human control, safety, and trust, while direct involvement of end users remained limited [39]. Learners and teachers are in a position to explain when a reminder becomes disruptive, why a label feels misleading, or which information is missing from an automated judgment. Including their perspectives in design and evaluation could help align interventions with the conditions of actual study and make disagreements about system recommendations visible.

UNESCO's guidance on generative AI in education calls for a human-centered approach that addresses privacy, ethical validation, age appropriateness, and pedagogical suitability [15]. For an online course, these principles have practical implications: students should be told which records are collected, why the information is needed, and how recommendations are generated. Where feasible, they should be able to change preferences or decline particular forms of automated assistance. Teachers and institutions also need a clear process for reviewing incorrect or inappropriate outputs.

How systems are evaluated will influence how they are developed. A rise in login frequency or task completion may indicate greater participation, but it may also reflect persistent prompting without improved understanding. Assessment therefore needs to consider learning outcomes and activity records alongside learners' experiences of confidence, autonomy, trust, and the ability to regulate their work over time. These measures would help distinguish interventions that make a course more active from those that make learning more manageable and meaningful.

E. Limitations and Directions for Future Research

The framework is based on conceptual synthesis and has not been tested with new learner data. Its five categories of barriers and five areas of AI-supported design describe theoretically grounded relationships that require empirical examination. Literature was selected for conceptual relevance, without a formal database search and screening protocol. The framework therefore remains open to perspectives beyond those included in this synthesis.

Relationships among the psychological processes identified here remain to be investigated in specific online learning settings. Survey data and structural equation modeling could examine, for instance, whether self-efficacy helps explain a relationship between self-regulation and persistence, or whether belonging mediates participation in online discussion. Research might also explore how cognitive load and learning fatigue relate to repeated interruptions. These analyses would help establish which connections are supported empirically and where the proposed categories require adjustment.

The individual design proposals also lend themselves to testing within courses. Studies could compare the experience of returning to an interrupted lesson with and without a short resumption prompt, examine how students use adaptive recommendations, or assess the effects of different forms of feedback on subsequent task performance and confidence. Quasi-experimental and design-based approaches could be combined with longer observation periods, given the uncertainty surrounding sustained effects of dashboards and automated feedback [11,12]. Interviews, learning diaries, and participatory design would add information about why students ignore a reminder, hesitate to enter a discussion, or distrust a suggestion—experiences that are difficult to interpret from platform activity alone.

The discussion concentrates on higher education, adult learning, and vocational training. The needs of younger students, who may depend more heavily on teachers and parents, may lead to different approaches to supervision and guidance. Educational disciplines, cultural settings, and learners' previous experience with technology may also affect which forms of assistance are appropriate. Testing the framework across these settings could clarify how much of its structure is transferable and which design choices require local adaptation.

CONCLUSION

Online learning gives students access to education under more flexible conditions while often requiring them to organize study, recover from interruptions, seek interaction, and interpret their progress with less immediate assistance. Drawing on applied educational psychology, this paper examined how these demands affect participation and persistence

and developed a conceptual framework linking learners' needs to possible forms of AI support. The framework considers adaptive guidance, assistance after interruptions, collaboration support, formative feedback, and pathways responsive to learners' circumstances.

The proposed uses of AI depend on choices about what information is collected, how recommendations are explained, and when teachers or learners should make the final judgment. Assistance is most useful when it gives students a clearer basis for deciding how to proceed and leaves them able to revise that decision. Teacher involvement and transparent data practices remain essential to the practical application of the framework.

Further studies will need to establish which proposed connections hold in different courses and whether particular AI functions improve learning, confidence, interaction, and longer-term self-regulation. Combining activity records with learners' accounts of their experiences would be especially valuable for examining the reasons behind participation and interruption. Such evidence could help refine the framework and inform designs that learners and teachers can use and assess in everyday educational settings.

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