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Emotion-aware learning analytics dashboards: Effects on metacognitive regulation, academic performance, and engagement in self-paced MOOCs

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ABSTRACT

Learning analytics dashboards are widely used in self-paced online courses, yet many still emphasize progress and activity while giving limited attention to learners' emotional states and real-time self-regulation. This study examined whether an emotion-aware learning analytics dashboard (EALAD) could improve learners' metacognitive regulation, academic performance, and multidimensional engagement in a self-paced massive open online course (MOOC), compared with a standard learning analytics dashboard (LAD) and a no-dashboard condition. Using a randomized controlled design, 150 undergraduate students from three Iranian universities were assigned to an emotion-aware dashboard group (EDG), a standard dashboard group (SDG), or a control group (CG). The three-month intervention was implemented in a self-paced MOOC on instructional design, and all participants were selected from the intermediate range of the Oxford Quick Placement Test (OQPT), with scores between 31 and 40. Data were collected through the Metacognitive Awareness Inventory, an academic performance test, a multidimensional engagement questionnaire, and follow-up interviews. Quantitative data were analyzed using mixed-design and one-way ANCOVAs while controlling for pretest scores. The EDG showed the strongest gains across outcomes, including metacognitive regulation, partial $\eta^2 = 0.596$; emotional engagement, partial $\eta^2 = 0.500$; cognitive engagement, partial $\eta^2 = 0.463$; and academic performance, partial $\eta^2 = 0.417$, outperforming both the SDG and CG. The interview findings further showed that the EALAD helped learners recognize emotional states, respond to difficulties more promptly, and interpret progress more holistically. Participants viewed the standard dashboard as useful for pacing and progress tracking, but less helpful for understanding engagement quality. The findings suggest that integrating real-time emotional indicators with actionable dashboard prompts can support self-regulatory decision-making, meaningful engagement, and achievement in self-paced MOOC environments.

1. Introduction

The rapid growth of massive open online courses (MOOCs) has expanded access to flexible learning, but it has also intensified concerns about sustaining learners' motivation, self-regulation, and engagement in self-paced environments [1,2]. Because learners often study with limited real-time instructor support, they may struggle to monitor progress, adjust strategies, and maintain persistence over time [3]. Learning analytics dashboards (LADs) have been introduced as one response to these challenges because they can visualize progress and performance and support metacognitive monitoring. However, many LADs remain largely descriptive and do not consistently help learners translate analytics into actionable self-regulatory decisions [4]. Reviews of dashboard research also show that student-facing LADs have mainly emphasized behavioral traces, such as time, activity, and clicks, as well as cognitive or performance indicators, such as scores and completion, while affective information has often been limited or weakly integrated [5,6]. This gap is important because achievement emotions shape attention, strategy use, persistence, and engagement quality, especially when learners must regulate their study with minimal instructional mediation [7,8].

Affective learning analytics extends conventional learning analytics by considering learners' emotional states alongside cognitive and behavioral evidence [9,10]. Drawing on affective computing, such systems can infer emotional states from multimodal traces, including facial expressions, voice, interaction patterns, and physiological signals, and then present these inferences as interpretable indicators for feedback and adaptive support [11,12]. Recent advances in artificial intelligence, sensor technologies, and human-computer interaction have further strengthened the feasibility of systems that detect, represent, and

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respond to emotional dynamics in real time [13]. This capability is particularly relevant in self-paced MOOCs, where frustration, boredom, or anxiety can undermine persistence, while timely affect-aware feedback may help learners sustain motivation and engagement.

Evidence from large-scale MOOC research also indicates that self-regulated learning (SRL) profiles are closely related to persistence, engagement, and goal attainment. Kizilcec et al. [14], for example, found that goal setting and strategic planning were associated with stronger goal attainment in MOOCs. Because self-paced MOOCs require learners to manage time, effort, and learning pathways with limited external structure, systems that strengthen SRL processes may be especially valuable.

Emotion-aware learning analytics dashboards (EALADs) represent one practical form of such support. In the present study, an EALAD is defined as a learning analytics dashboard that integrates affective-state indicators, generated through emotion recognition and related affective analytics, with behavioral learning traces to provide real-time visualizations and personalized prompts. These features are intended to help learners monitor, interpret, and regulate both learning progress and emotional states during task engagement. By combining emotional feedback with traditional learning metrics, EALADs can offer a more multidimensional view of progress and support learner self-regulation and instructional adaptation [15,16]. Unlike standard dashboards that mainly emphasize pacing and task completion, EALADs are designed to promote affective awareness, adaptive regulation, and personalized feedback over time [4].

The mechanism underlying EALADs can be understood as a closed-loop cycle. First, affective cues are detected and summarized into interpretable dashboard indicators. Second, these indicators are presented with progress and behavioral traces to help learners diagnose their current learning state. Third, the system provides timely, strategy-oriented prompts aligned with the learner's state and task demands, such as adjusting pace, taking a strategic break, revisiting difficult content, seeking help, or reallocating effort. Finally, learners' responses and trace data feed back into the dashboard and inform later prompts, allowing personalization across learning episodes [17,18]. Empirical evidence suggests that emotion-aware dashboards can support SRL strategies, motivation, and engagement [19,20]. Zheng et al. [20] showed that interventions informed by dashboard emotion data could increase learner persistence, while Valle et al. [21] found that predictive dashboards combined with task-value scaffolding helped reduce the effects of negative affect, including statistics anxiety.

The potential value of EALADs is especially clear for metacognitive regulation, which refers to the planning, monitoring, and evaluation processes through which learners supervise and adjust their cognitive activity [22]. In technology-supported learning environments, metacognitive regulation has been linked to stronger learning outcomes because learners often need to respond to difficulties without immediate instructor input [23,24]. From an SRL perspective, Pintrich [25], Winne and Hadwin [18], and Zimmerman [26] suggest that learners benefit when feedback helps them monitor their state and choose appropriate strategies. Affective cues may therefore function as diagnostic signals that sharpen metacognitive monitoring and control, especially when dashboards reduce the uncertainty of deciding what to do next. Tools that make both cognitive and affective states visible can support more calibrated self-assessment and strategic adjustment [27,28]. Because metacognitive regulation is also associated with academic achievement and can support resilience, motivation, and lower anxiety in language and online learning contexts, EALADs may also contribute to performance gains [29,24,30].

Academic performance in technology-rich learning environments is shaped by interacting cognitive, behavioral, emotional, and contextual factors, which makes improvement more likely when regulation and engagement are strengthened together rather than treated as isolated outcomes [31,32]. In online and blended learning, SRL strategies have consistently been associated with higher achievement, as Zhao et al. [33] also reported. At the same time, digital engagement supports learning only when it is purposeful and well regulated, since participation alone does not guarantee achievement gains [34–36]. Interventions that foreground self-monitoring, adaptive feedback, and structured self-evaluation have been shown to improve learning by strengthening metacognitive awareness and motivation [37,38]. From this perspective, EALADs may improve performance in self-paced MOOCs because they are positioned to support regulation and engagement at the same time.

Engagement is commonly understood as a multidimensional construct that includes behavioral, cognitive, and emotional dimensions, and it remains central to learning success in online environments [39]. In MOOCs, engagement shapes persistence, learning depth, and the effectiveness of instructional interventions [40,41]. Schiller et al. [42,43] found that stronger behavioral engagement, often reflected in interaction logs, was associated with more favorable learning outcomes, and Liu et al. [44] showed that sustained participation in MOOC discussions can predict achievement. Nonetheless, disengagement continues to challenge large-scale online learning, particularly when learners perceive limited interactivity or weak relevance to their goals [45]. Because engagement quality is sensitive to learners' moment-to-moment appraisals and emotions, dashboards that make affective information visible and interpretable may be especially useful for sustaining meaningful participation in self-paced MOOCs.

Although EALADs are theoretically promising, their empirical value in MOOCs requires clearer specification. In particular, more evidence is needed on whether emotion-aware dashboards offer measurable advantages over standard dashboards and how affect-aware feedback may support metacognitive regulation, multidimensional engagement, and academic performance. The present study is informed by SRL perspectives [25,26] and by accounts that emphasize the functional role of achievement emotions [7], with control-value theory of achievement emotions serving as the central theoretical frame. Pekrun [7,46] and Pekrun and Perry [8] explain that learners' appraisals of control and value shape achievement emotions, which then influence strategy use, engagement quality, and performance. Accordingly, this study advances an integrated account in which emotion-aware feedback is expected to strengthen metacognitive monitoring and control, support multidimensional engagement, and improve academic performance in self-paced learning. The study evaluates the effects of EALADs in comparison with a standard dashboard and a no-dashboard control condition in a self-paced MOOC, using both quantitative and qualitative evidence to inform the design of affect-aware learning environments.

2. Theoretical and empirical background of the study

The use of EALADs in self-paced MOOCs can be understood through complementary theories that explain how emotional, cognitive, and motivational processes shape learning. Within SRL theory, learners are viewed as active agents who set goals, monitor progress, manage cognition and motivation, and adapt strategies to improve learning [25,26]. Successful self-paced learning therefore depends strongly on metacognitive regulation, including planning, monitoring, and evaluating learning processes [47,48]. EALADs can support these processes by integrating emotional and behavioral information into timely, individualized feedback that helps learners notice their internal states, interpret their progress, and make more calibrated adjustments during study [49]. This support is particularly relevant in self-paced MOOCs, where learners must often decide independently when to pause, revisit content, regulate frustration, or sustain effort. From a cognitive-science perspective, this pathway is also consistent with evidence that emotions influence attention, working memory, executive control, and memory consolidation, all of which affect what learners notice, process, and retain [50–52].

Metacognition theory further clarifies why emotion-aware feedback may matter for autonomous online learning. Flavell [53] conceptualized metacognition as learners' awareness and regulation of their own cognitive processes, and Schraw and Dennison [54] distinguished between metacognitive knowledge and metacognitive regulation. In this tradition, metacognitive knowledge concerns what learners know about their strengths, weaknesses, and strategies, while metacognitive regulation involves the deliberate management of attention, effort, and strategy use [55]. EALADs can strengthen metacognitive activity by displaying learners' emotional experiences alongside behavioral and progress indicators [56]. For example, learners may better recognize how confusion, boredom, or anxiety coincides with reduced concentration, weaker persistence, or declining motivation. In this way, dashboards can make the emotional dimension of learning more visible and open to regulation, an area that has often received less explicit attention in conventional instructional settings [57].

Importantly, negative affect should not be treated as uniformly harmful. D'Mello and Graesser [58] argue that confusion can sometimes signal productive disequilibrium, especially when learners receive adequate support to resolve misunderstanding. Similarly, Kapur [59] showed that productive struggle can support deeper learning when appropriately structured. However, persistent boredom or anxiety may weaken perceived control, narrow attention, and contribute to disengagement when learners lack timely strategies for restoring productive effort [60,7]. For this reason, the value of EALADs lies not in removing all negative emotion, but in helping learners distinguish productive struggle from escalating unproductive affect and choose timely regulation strategies.

Affective computing provides the technological basis for this kind of support. Picard [11] introduced affective computing as an approach to designing systems that can sense, interpret, and respond to human emotions. In educational technology, this work has informed emotion-aware learning systems that use observable and physiological cues, such as facial expressions, vocal features, and bodily responses, to infer learners' affective states [12]. EALADs extend these capabilities by presenting real-time emotional feedback together with familiar learning analytics indicators. Han et al. [61] suggest that such feedback can be especially useful when learners encounter demanding content or begin to disengage, because it can help them recognize affective changes before motivation and persistence decline. Methodologically, affective computing in learning contexts often involves data capture from sources such as facial behavior, speech prosody, interaction logs, eye-gaze proxies, electrodermal activity, or heart-rate variability, followed by feature extraction, model-based inference, and multimodal fusion [62]. Yadegaridehkordi et al. [63] emphasize that the value of these systems depends on transparent labeling, contextual sensitivity, and clear alignment between inferred affective states and learning-relevant constructs. Thus, affect sensing is educationally meaningful only when dashboard indicators are interpretable, instructionally useful, and connected to feasible regulation options.

Cognitive load theory also helps explain the potential role of EALADs in self-paced learning. Learning is most effective when working-memory demands are managed in ways that preserve capacity for germane processing and schema construction [64–66]. In technology-mediated environments, anxiety, frustration, and boredom can increase extraneous load and reduce learners' ability to process and integrate new information [67]. From this standpoint, EALADs may support learning by alerting learners to unproductive affect and offering prompts that help regulate effort, pacing, and task approach before cognitive demands become overwhelming. For instance, when confusion is detected, a dashboard may suggest revisiting prerequisite content, slowing down, or taking a brief reflective break [68]. At the same time, because confusion can also promote deeper processing when it remains manageable, EALADs should support resolution-oriented regulation without interrupting productive struggle too early [58,59].

Among the relevant theoretical perspectives, control-value theory (CVT) of achievement emotions offers the most direct rationale for EALADs. CVT explains that achievement emotions arise from learners' appraisals of control and value and then influence attention, engagement, strategy use, and performance [7,46,8]. In self-paced MOOCs, perceived control may decline when task difficulty increases, while perceived value may weaken when activities feel repetitive or disconnected from learners' goals. EALADs are therefore positioned to support learning by making emotional states visible, linking them to behavioral traces, and prompting timely regulation, such as slowing down, revisiting content, taking restorative breaks, or reallocating effort. Self-determination theory is also relevant because dashboards may protect learners' autonomy and competence, which are important for persistence [69–72]. However, the present intervention is anchored mainly in CVT because it focuses specifically on the detection, interpretation, and regulation of achievement emotions during learning.

Taken together, these perspectives support a dashboard-to-outcome pathway in which EALAD effects depend on three connected processes. First, dashboards increase awareness of learning-relevant emotional and behavioral signals. Second, learners interpret those signals in relation to goals, progress, and task demands. Third, learners select and enact appropriate strategies. Jivet et al. [17], Verbert et al. [73], and Winne and Hadwin [18] similarly emphasize that dashboard feedback becomes meaningful when it supports awareness, sense-making, and action. This pathway also explains why dashboards may sometimes change engagement behaviors without immediately improving performance. Feedback may increase awareness and reflection, but performance gains are more likely when learners can translate feedback into concrete strategic action [7,25].

Empirical evidence supports this interpretation while also showing that dashboard effects depend on design quality. Han et al. [61] examined LADs in face-to-face collaborative argumentation (FCA) over four weeks with 88 university students. They used two adaptive dashboards, one for helping students monitor collaboration and another for helping teachers provide timely intervention. The results showed improvements in FCA outcomes and student engagement, and participants generally perceived the dashboards as usable and useful. These findings suggest that adaptive dashboards can support metacognitive regulation and engagement by making learning-relevant signals more visible and by enabling more timely feedback. At the same time, broader reviews caution that dashboard effects vary according to framing, comparison features, and the extent to which analytics are translated into actionable recommendations [5,6].

Further evidence comes from studies of motivational and performance-oriented dashboard features. Fleur et al. [74] conducted two randomized controlled trials in higher education, including one online course during the COVID-19 pandemic, to examine the effects of social comparison features in LADs. Their dashboards displayed learners' actual and predicted performance alongside peer comparisons and produced meaningful gains in extrinsic motivation and academic achievement, although changes in metacognitive ability were not statistically significant. This pattern suggests that performance-focused dashboards may energize effort and goal striving, but they may not improve metacognitive functioning unless they explicitly prompt monitoring and control. Toyokawa et al. [75] reported a similar process-oriented pattern in secondary education. Their Active Reading Dashboard (AR-D) helped high school English learners display more effective learning behaviors, even though vocabulary and reading comprehension gains were similar across groups. These findings indicate that dashboards can shape engagement and self-regulatory habits even when achievement effects are less immediate, especially when the intervention primarily influences learning processes rather than content mastery. In line with this view, feedback is most likely to support robust outcomes when it helps learners move from awareness to timely strategy adjustment [17,25].

Recent language-learning research also highlights the importance of specific dashboard features. Geng and Yamada [76] developed a learning analytics dashboard for intermediate learners of Japanese that combined personal learning data, social comparison features, and visualizations of learning processes. In a sample of 31 participants, they found significant gains in knowledge acquisition and metacognitive awareness. Learners who attended more closely to social comparison and process visualizations tended to show stronger knowledge retention, while those who focused on personal learning data showed greater metacognitive development. This pattern shows that dashboards should not be treated as uniform interventions. Their effects depend on the information made salient, learners' interpretation of that information, and the availability of regulation options that remain actionable under emotional pressure [7,26].

Overall, the theoretical and empirical evidence suggests that EALADs can support metacognitive regulation, motivation, engagement, and, in some cases, academic performance when feedback is timely, actionable, and emotionally contextualized. This makes EALADs especially promising for self-paced MOOCs, where learner autonomy is high and external guidance is limited. However, their value should not be reduced to visualization alone. EALADs are best understood as regulation-oriented systems whose effectiveness depends on how affective and behavioral indicators are converted into interpretable guidance for monitoring, sense-making, and strategy enactment across learning episodes [17,73].

2.1. Research gap and questions

Despite growing interest in EALADs, important gaps remain in understanding their value for self-paced MOOCs, particularly among Iranian English as a Foreign Language (EFL) learners. Much existing research has examined dashboard use in general higher education or broader online-course contexts mainly outside this population, leaving culturally and linguistically diverse learners comparatively under-examined. This gap is important because self-paced MOOCs place strong demands on SRL, and Kizilcec et al. [14] showed that learners' SRL profiles are meaningfully associated with engagement trajectories and goal attainment. Although prior studies have reported benefits for motivation and engagement, fewer studies have simultaneously examined the effects of EALADs on metacognitive regulation, engagement, and academic achievement in English-medium instructional-design MOOCs involving Iranian EFL learners.

Another limitation concerns explanatory clarity. Dashboard studies often report outcome differences without specifying which part of the learning mechanism has changed, such as learners' awareness of learning-relevant signals, their interpretation of those signals, or their subsequent strategic actions. This lack of precision makes it difficult to explain null or mixed findings across contexts [5,17,6]. In addition, many dashboards still emphasize cognitive and behavioral analytics while giving less attention to emotional feedback that is sensitive to learners' affective and motivational needs. This issue is especially relevant for Iranian EFL learners studying disciplinary content through English-medium self-paced MOOCs, where self-regulation demands, anxiety, and motivational fluctuation may shape learning engagement [77,78]. From the perspective of achievement emotions, such learners may experience shifting control and value appraisals during English-mediated instructional-design tasks, which can influence strategy use, engagement quality, and performance [7,8].

Accordingly, Iranian EFL learners enrolled in an English-medium instructional-design MOOC provide a meaningful context for examining whether EALADs can support affective awareness, metacognitive regulation, and sustained engagement rather than merely tracking behavioral progress. This context also allows closer attention to cognitive-affective states such as confusion, which may support productive sense-making when learners receive guidance for resolution and strategy adjustment, but may undermine learning when it develops into persistent negative affect [58,60].

To address these gaps, the present study examines whether an EALAD can support Iranian EFL learners' metacognitive regulation, academic performance, and behavioral, cognitive, and emotional engagement in an English-medium, self-paced instructional-design MOOC. The study treats these outcomes as interrelated components of a single explanatory pathway. Specifically, EALAD feedback is expected to enhance learners' affective awareness and help them interpret their learning states more clearly. This awareness is expected to strengthen metacognitive monitoring and control, support sustained multidimensional engagement, and contribute to stronger academic performance. The following research questions guided the study:

RQ1. To what extent does access to an EALAD influence Iranian EFL learners' metacognitive regulation in an English-medium, self-paced instructional-design MOOC compared with a standard dashboard or no dashboard?
RQ2. To what extent does access to an EALAD affect Iranian EFL learners' academic performance in an English-medium, self-paced instructional-design MOOC?
RQ3. To what extent does access to an EALAD influence Iranian EFL learners' behavioral, cognitive, and emotional engagement in an English-medium, self-paced instructional-design MOOC?
RQ4. How do learners perceive the contribution of EALADs to self-paced MOOC learning, metacognitive regulation, and engagement?

3. Method

3.1. Participants

A total of 150 undergraduate EFL learners from three Iranian universities participated voluntarily in the study. All participants were enrolled in an English-medium, self-paced MOOC on instructional design. Their ages ranged from 18 to 32 years (EDG: 18 to 32 years, $M = 24.7$, $SD = 3.8$; SDG: 18 to 31 years, $M = 24.5$, $SD = 4.0$; CG: 19 to 32 years, $M = 24.6$, $SD = 3.9$; overall: $M = 24.6$, $SD = 3.9$), and the sample included 78 female and 72 male learners (EDG: 26 female, 24 male; SDG: 26 female, 24 male; CG: 26 female, 24 male). To ensure broadly comparable English proficiency across groups, all participants completed the Oxford Quick Placement Test (OQPT) before the intervention. Only learners who scored between 31 and 40, corresponding to the intermediate proficiency band, were included.

The target sample size was determined before recruitment to support reliable comparisons across the three experimental conditions. Following Cohen's [79] guidance for detecting medium effects in group-based designs, and using standard power-analysis procedures for regression-family tests [80], a balanced sample of approximately 50 participants per condition was considered appropriate. Consistent with Lakens [81], the planned N was treated as the minimum sample expected to provide decision-relevant evidence while supporting stable estimation of adjusted group means. The final allocation therefore included 50 participants in the emotion-aware dashboard group (EDG), 50 in the standard dashboard group (SDG), and 50 in the control group (CG). This balanced structure also helped preserve precision for pairwise comparisons and allowed for the possibility of attrition, which is common in self-paced online learning.

Recruitment was conducted through course announcements, and participation was voluntary. After eligibility screening, participants provided written informed consent and were randomly assigned to the EDG, SDG, or CG using stratified randomization by gender. Ethical approval was obtained from a state-run university. Participants in the EDG also gave explicit consent for the use of facial emotion recognition during the intervention. They were informed that facial video data would be processed in real time, anonymized immediately after feature extraction, and deleted after the analyses were completed. All participants were also told that they could withdraw from the study at any point without penalty.

The sample was drawn from a defined population of intermediate-level undergraduate EFL learners in Iranian universities who were willing to participate in an English-medium, self-paced MOOC. This sampling structure strengthened internal comparability, particularly by reducing large proficiency differences, but it also limits the scope of generalization. Because participants were recruited voluntarily from the participating universities, the sample is best understood as a convenience sample from this educational context. As Bornstein et al. [82] note, self-selection may reflect motivation, availability, or interest in technology-supported learning. Accordingly, the findings should be interpreted primarily as evidence about differences among the three instructional conditions within the observed setting. Broader generalization should be tested through replication across additional institutions, proficiency levels, and cultural contexts, as emphasized in discussions of representativeness in educational and behavioral research [83]. Transparent reporting of the sampling approach and sample-size rationale also strengthens the interpretability of controlled comparisons within a defined population [81]. (Table 1).

3.2. Instruments

The first instrument was the OQPT, which was used to screen participants' English proficiency before the intervention. The OQPT includes 60 multiple-choice items assessing grammar, vocabulary, and reading comprehension, and its scores are mapped onto the Common European Framework of Reference for Languages (CEFR) bands. In the present study, only learners who scored between 31 and 40, corresponding to the intermediate level, were included. This procedure helped ensure a broadly comparable language proficiency level across the three experimental groups.

The second instrument was the Behavioral, Cognitive, and Emotional Engagement Questionnaire, adapted from Al-Obaydi et al. [84]. The questionnaire measured engagement as a multidimensional construct through three subscales: behavioral engagement with 11 items, cognitive engagement with 12 items, and emotional engagement with 12 items. Items were rated on a five-point Likert scale ranging from strongly disagree to strongly agree. Before the main study, the adapted questionnaire was piloted with 31 EFL learners comparable to the target population. The pilot confirmed item clarity and contextual suitability, and minor wording revisions were made to simplify complex phrases and improve the comprehensibility of several emotional engagement items. Reliability was satisfactory, with Cronbach's alpha values of 0.87 for behavioral engagement, 0.83 for cognitive engagement, and 0.85 for emotional engagement. Content validity was supported by three EFL professionals, and exploratory factor analysis confirmed the intended three-factor structure. The use of this multidimensional measure was appropriate because engagement is commonly understood as behavioral, cognitive, and emotional in nature, and these dimensions provide richer evidence than platform logs alone [85].

The third instrument was the Metacognitive Awareness Inventory (MAI), developed by Schraw and Dennison [54]. The MAI includes 52 items representing two broad components: knowledge of cognition and regulation of cognition. In this study, the MAI was administered at pretest and posttest using a five-point Likert-type response format, yielding a possible total score range of 52 to 260, with higher scores indicating stronger metacognitive awareness and regulation. The instrument was selected because it directly captures planning, monitoring, and strategic control, which align with the study's emphasis on self-paced learning and metacognitive regulation. Schraw and Dennison [54] reported strong psychometric properties for the MAI, and self-report measures of metacognition remain widely used in technology-supported learning research [86–88]. Total scores were computed by summing the 52 item responses after reverse-coding negatively keyed items where applicable, and internal consistency was evaluated using Cronbach's alpha = 0.84, which is appropriate for multi-item Likert-type scales. Validity interpretation was supported by preserving the original construct mapping and examining whether item clusters aligned with the two MAI components.

Table 1
Participant characteristics.

Characteristic	EDG	SDG	CG	Total
N	50	50	50	150
Age range	18 to 32	18 to 31	19 to 32	18 to 32
Age, M (SD)	24.7 (3.8)	24.5 (4.0)	24.6 (3.9)	24.6 (3.9)
Female, n	26	26	26	78
Male, n	24	24	24	72
Universities represented	3	3	3	3
Eligibility based on OQPT band	31 to 40	31 to 40	31 to 40	31 to 40

NOTE. M = mean; SD = standard deviation; EDG = emotion-aware dashboard group; SDG = standard dashboard group; CG = control group; OQPT = Oxford Quick Placement Test.

Academic performance was measured through a researcher-developed reading comprehension test aligned with the learning objectives of the instructional design MOOC. The test included 60 items covering key course topics and was designed to assess learners' course-relevant knowledge and skills. To capture different levels of cognitive demand, it included multiple-choice questions, true or false items, and short-answer questions. The test was piloted with 30 learners from a comparable population to check clarity, difficulty, and administration time, and minor revisions were made accordingly. Content validity was reviewed by instructional design faculty and language assessment specialists. Scores were standardized to a total of 30 points, with items weighted proportionally. Reliability evidence indicated good internal consistency, with Cronbach's alpha of 0.87. The test was administered at both pretest and posttest to examine baseline comparability and compare academic performance across the three conditions after the intervention.

Finally, semi-structured interviews were conducted after the intervention to obtain a richer account of learners' experiences. Interviewees were selected through criterion-based purposive sampling with a maximum-variation logic [89]. Participants were eligible for interviews if they completed the intervention and posttest measures, consented to follow-up interviews, and represented different engagement and performance profiles within each condition. Selection also considered variation in learning trajectories, such as sustained or fluctuating participation, and sought gender balance where volunteer availability allowed. The interview protocols were tailored to each group. EDG participants reflected on real-time emotional feedback and the integration of facial emotion data with clickstream information. SDG participants discussed clickstream-based progress feedback and its role in engagement and self-monitoring. CG participants described learning without dashboard support and the strategies they used for self-regulation and emotional management. Each interview lasted approximately 30 to 45 min, was audio-recorded with consent, and was transcribed for thematic analysis. In total, 27 interviews were conducted, with nine participants from each group, and sampling ended when thematic patterns became stable within and across conditions.

3.3. Treatment for each group

Participants were assigned to one of three conditions during a three-month, self-paced MOOC on instructional design. The course included 10 reading texts with related comprehension checks and reflection tasks. To ensure consistent instructional exposure, all groups completed the same texts in the same order, used the same MOOC platform, followed the same deadlines, and worked under identical scoring rules and assessment windows. The texts were selected and reviewed in advance to ensure comparable topic relevance, length, and expected difficulty. Following intervention-reporting guidance, the treatment components, delivery features, and fidelity-relevant procedures were specified to support replication [90]. Learners were expected to complete approximately one text per week during the first 10 weeks, while the remaining weeks were used for consolidation and posttest completion. The expected weekly workload was approximately 2 to 3 h.

In the emotion-aware dashboard group (EDG, n = 50), learners accessed the MOOC through an EALAD. The dashboard integrated real-time emotional feedback from FaceReader emotion recognition software with clickstream-based learning traces. FaceReader analyzed facial expressions during study and generated indicators of emotional states such as frustration, confusion, boredom, and engagement. These affective indicators were combined with behavioral traces, including time on task, navigation patterns, repeated backtracking, rapid skipping, inactivity, and comprehension-check attempts. The EALAD then presented learners with an integrated view of their learning progress and emotional engagement.

The EDG dashboard also delivered personalized, strategy-oriented prompts to support metacognitive regulation. These prompts were generated through a rule-based logic that combined affective signals with behavioral evidence, and each prompt was logged with its timestamp and trigger pattern, consistent with Hoffmann et al.'s [90] emphasis on transparent intervention reporting. Prompts were delivered in two formats: a brief on-screen notification and a persistent next-step panel with a short recommendation and a one-click link to a relevant support feature, such as a glossary entry, recap, or optional practice item. Prompt content focused on three regulation goals. Comprehension-repair prompts encouraged learners to reread, summarize, or revisit difficult sections. Pacing and effort-recalibration prompts guided learners to slow down, monitor understanding, or complete a self-check before continuing. Affect-regulation prompts suggested actions such as taking a brief break and returning to a recap or example item when confusion or frustration persisted.

To reduce unnecessary interruptions, prompts were issued only when an affective indicator exceeded a predefined threshold for a minimum continuous period and at least one behavioral marker also suggested struggle or disengagement. For example, confusion or frustration prompts required signs such as unusually prolonged time on task, repeated backtracking, or repeated incorrect attempts. Disengagement prompts were triggered by extended inactivity or rapid page transitions with limited dwell time. Boredom prompts required boredom signals together with accelerated scrolling or repeated fast transitions. Prompts were rate-limited through a cooldown interval, and learners could dismiss them without penalty. Dismissals and follow-up actions were recorded in system logs to support fidelity interpretation [90].

In the standard dashboard group (SDG, n = 50), learners used a conventional dashboard based only on clickstream analytics. The SDG dashboard displayed progress through the 10 texts, time on task, per-text completion status, navigation summaries, and comprehension-check scores. These indicators were shown through a progress bar, per-text summary table, and simple trend visuals for cumulative time and quiz performance. The SDG interface was kept as similar as possible to the EDG interface, except that it did not include any affective panel, emotion indicators, personalized prompts, or adaptive recommendations. This design preserved treatment separation while allowing the study to compare the added value of emotion-aware feedback beyond

Recruitment (MOOC announcements)

↓

Eligibility screening (OQPT; intermediate band 31–40)

↓

Informed consent (FaceReader consent included for EDG)

↓

Pretest (Engagement + MAI)

↓

Stratified randomization by gender

↓

3-month intervention (10 reading texts + identical tasks across groups)

• EDG: EALAD enabled (FaceReader + clickstream) → personalized prompts

• SDG: Standard dashboard (clickstream only; no emotion data; no personalized prompts)

• CG: No dashboard (platform access only; no analytics feedback)

↓

Posttest (Engagement + MAI + academic performance test)

↓

Interviews (n = 27; nine per group)

↓

Thematic analysis

Fig. 1. Study design and intervention flowchart.

standard progress tracking.

In the control group (CG, n = 50), learners completed the same 10 reading texts, comprehension checks, and reflection activities without any dashboard support. They accessed the same instructional materials and followed the same assessment windows as the EDG and SDG, but all analytics feedback, real-time monitoring, visual summaries, and automated prompts were disabled. Thus, the CG represented independent self-paced MOOC participation without dashboard-based support. (Fig. 1)

3.4. Data analysis

Quantitative analyses were conducted in SPSS version 26. Before hypothesis testing, the data were screened for missing values, outliers, influential cases, and the main assumptions of covariate-adjusted models. Distributional normality was examined using Kolmogorov-Smirnov tests, and homogeneity of variances was assessed through Levene's test. Linearity between each covariate and its corresponding outcome, as well as the homogeneity of regression slopes across groups, was also checked before estimating the main models.

For metacognitive regulation and engagement outcomes, mixed-design ANCOVA models were used, with the relevant pretest scores entered as covariates. Academic performance was analyzed using one-way ANCOVA, with OQPT scores controlled to adjust for baseline proficiency differences. In each model, Group, including EDG, SDG, and CG, was entered as the fixed factor. To control residual baseline variability and strengthen interpretability, pretest scores and relevant covariates were included in the analyses. Because several outcomes were examined, a multivariate omnibus test using Pillai's Trace was conducted first. When the omnibus Group effect was significant, follow-up univariate ANCOVAs were performed for each dependent variable.

Statistical significance was evaluated at $\alpha = 0.05$ using two-tailed tests. In line with contemporary quantitative reporting standards, F values, degrees of freedom, exact p values where available, and partial η^2 values were reported [91,92]. Cumming [93] emphasized the value of estimation-focused reporting; accordingly, 95% confidence intervals were reported for adjusted posttest means and adjusted mean differences. When significant Group effects were found, Bonferroni-adjusted pairwise comparisons were used to identify differences among EDG, SDG, and CG while controlling the familywise error rate. To reduce time-related confounding during the three-month intervention, instructional content, task sequence, assessment windows, and learning conditions were held constant across groups, except for the dashboard features assigned to each condition. Analytic sample sizes were reported with the results tables to support transparency and reproducibility.

Qualitative interview data were analyzed through thematic analysis following Braun and Clarke's [94] six-phase procedure. The transcripts were first read repeatedly to support familiarization with the data. Initial codes were then generated, organized, reviewed, and refined into themes. An initial codebook was developed through open coding and applied systematically across all transcripts, with refinements documented during the analytic process. To strengthen trustworthiness, coding decisions and emerging themes were peer reviewed by two researchers, and member checking was used to confirm the interpretive adequacy of the final themes.

4. Results

The results are presented in two parts: quantitative findings addressing RQs 1–3, and qualitative findings addressing learners' perceived contribution of dashboard support to self-paced MOOC learning, addressing RQ4.

Preliminary screening supported the use of the planned covariate-adjusted analyses. The dataset contained no missing responses for the variables included in the main models. Standardized residuals were within acceptable limits, with all values below $|3.00|$, and Cook's distance values were below 1.00, indicating that no case had a disproportionate effect on the results. Residual distributions were acceptable for behavioral engagement, Kolmogorov-Smirnov $D = 0.061$, $p = .200$, Shapiro-Wilk $W = 0.987$, $p = .176$; cognitive engagement, Kolmogorov-Smirnov $D = 0.058$, $p = .200$, Shapiro-Wilk $W = 0.989$, $p = .241$; emotional engagement, Kolmogorov-Smirnov $D = 0.064$, $p = .200$, Shapiro-Wilk $W = 0.984$, $p = .092$; metacognitive regulation, Kolmogorov-Smirnov $D = 0.052$, $p = .200$, Shapiro-Wilk $W = 0.991$, $p = .398$; and academic performance, Kolmogorov-Smirnov $D = 0.067$, $p = .200$, Shapiro-Wilk $W = 0.982$, $p = .061$. Levene's tests supported variance equality for behavioral engagement, $F(2, 147) = 1.184$, $p = .309$; cognitive engagement, $F(2, 147) = 0.927$, $p = .398$; emotional engagement, $F(2, 147) = 1.326$, $p = .269$; metacognitive regulation, $F(2, 147) = 1.541$, $p = .217$; and academic performance, $F(2, 147) = 0.884$, $p = .415$. Visual inspection of scatterplots indicated approximately linear relations between the covariates and posttest outcomes. The Group × pretest terms were not statistically significant for behavioral engagement, $F(2, 144) = 0.812$, $p = .446$; cognitive engagement, $F(2, 144) = 0.736$, $p = .481$; emotional engagement, $F(2, 144) = 1.094$, $p = .337$; and metacognitive regulation, $F(2, 144) = 0.968$, $p = .382$. The Group × OQPT term was also nonsignificant for academic performance, $F(2, 144) = 0.849$, $p = .430$. These preliminary results supported the use of the planned ANCOVA models.

Table 2 summarizes the descriptive statistics for behavioral engagement, cognitive engagement, emotional engagement, metacognitive regulation, and academic performance across the three groups at pretest and posttest. A close look at the pretest means shows that the groups began from broadly similar starting points. For behavioral, cognitive, and emotional engagement, the between-group differences were small and stayed within roughly one point, while metacognitive regulation and academic performance differed by no more than about two points. This pattern suggests that baseline levels were reasonably comparable prior to the intervention.

Table 2
Descriptive statistics for each dependent variable by group and time.

Variable	Group	Pretest M (SD)	Posttest M (SD)	N	Scale Range
Behavioral Engagement	EDG	37.88 (4.13)	47.70 (3.60)	50	11–55
Behavioral Engagement	SDG	36.02 (4.21)	44.08 (4.03)	50	11–55
Behavioral Engagement	CG	37.44 (4.66)	39.70 (4.29)	50	11–55
Cognitive Engagement	EDG	40.22 (4.17)	49.50 (3.58)	50	12–60
Cognitive Engagement	SDG	39.38 (4.12)	45.04 (3.95)	50	12–60
Cognitive Engagement	CG	39.18 (4.34)	40.92 (3.89)	50	12–60
Emotional Engagement	EDG	37.20 (3.84)	51.44 (4.29)	50	12–60
Emotional Engagement	SDG	38.42 (4.21)	46.04 (3.70)	50	12–60
Emotional Engagement	CG	39.10 (4.68)	41.70 (4.06)	50	12–60
Metacognitive Regulation	EDG	168.46 (11.63)	217.96 (11.75)	50	52–260
Metacognitive Regulation	SDG	167.88 (9.45)	200.24 (9.09)	50	52–260
Metacognitive Regulation	CG	169.32 (9.97)	187.62 (10.02)	50	52–260
Academic Performance	EDG	20.18 (2.35)	26.60 (2.25)	50	0–30
Academic Performance	SDG	19.12 (2.46)	24.28 (1.98)	50	0–30
Academic Performance	CG	19.32 (2.68)	22.44 (1.84)	50	0–30

NOTE. M = mean; SD = standard deviation; EDG = emotion-aware dashboard group; SDG = standard dashboard group; CG = control group.

By posttest, the pattern of scores became more differentiated. The EDG recorded the highest posttest means on all five measures and also displayed the most substantial gains across time. Behavioral engagement increased from 37.88 (SD = 4.13) to 47.70 (SD = 3.60), cognitive engagement rose from 40.22 (SD = 4.17) to 49.50 (SD = 3.58), and emotional engagement increased from 37.20 (SD = 3.84) to 51.44 (SD = 4.29). The increase in emotional engagement was particularly pronounced, exceeding 14 points, which is consistent with the expectation that real-time emotional feedback may be especially influential in sustaining learners' affective involvement during self-paced MOOC study. A similar pattern was observed for metacognitive regulation, which rose from 168.46 (SD = 11.63) to 217.96 (SD = 11.75), yielding the highest posttest level among the three conditions. Academic performance also improved markedly, increasing from 20.18 (SD = 2.35) to 26.60 (SD = 2.25), a score close to the upper bound of the 0–30 scale.

SDG also improved across outcomes, although the gains were consistently smaller than those of the EDG. Behavioral engagement increased from 36.02 (SD = 4.21) to 44.08 (SD = 4.03), and cognitive engagement rose from 39.38 (SD = 4.12) to 45.04 (SD = 3.95). Emotional engagement increased from 38.42 to 46.04, representing an improvement of approximately 7.6 points. Metacognitive regulation similarly increased from 167.88 (SD = 9.45) to 200.24 (SD = 9.09). Academic performance rose from 19.12 (SD = 2.46) to 24.28 (SD = 1.98), indicating meaningful progress, albeit not at the level observed in the emotion-aware condition.

In contrast, changes in CG, which received no dashboard support, were relatively modest over the same period. Behavioral engagement increased from 37.44 to 39.70, and cognitive engagement rose from 39.18 to 40.92. Emotional engagement moved from 39.10 to 41.70, while metacognitive regulation increased from 169.32 to 187.62. Academic performance showed a similarly small gain, rising from 19.32 to 22.44.

Overall, the descriptive trends point to a consistent pattern in which dashboard access was associated with greater improvements than the no-dashboard condition, and the emotion-aware dashboard was associated with the strongest gains across the measured outcomes. The differences are most visible for emotional engagement and metacognitive regulation, which accords with the study's rationale that affect-aware feedback, when paired with actionable guidance, can strengthen self-regulatory processes and help sustain engagement in self-paced online learning.

Table 3 reports the multivariate test of the Group effect using Pillai's Trace. After statistically controlling for pretest scores, the omnibus analysis showed a clear overall difference among the three conditions, namely the EDG, SDG, and CG, across the combined set of dependent variables, behavioral engagement, cognitive engagement, emotional engagement, metacognitive regulation, and academic performance, $V = 0.884$, $F(20, 278) = 11.020$, $p < .001$, partial $\eta^2 = 0.442$. Put differently, group membership accounted for about 44.2% of the adjusted multivariate variance in the outcome set. In light of commonly used benchmarks [95], this corresponds to a large multivariate effect and indicates that the form of dashboard support, whether emotion-aware, standard, or absent, was associated with substantial overall differences in learners' outcomes in the self-paced MOOC.

Table 4 reports the follow-up univariate ANCOVAs for each outcome at posttest, with the relevant covariate included in each model. The results show a consistent pattern across variables. For behavioral engagement, $F(2, 146) = 50.653$, $p < .001$, partial $\eta^2 = 0.408$, cognitive engagement, $F(2, 146) = 63.478$, $p < .001$, partial $\eta^2 = 0.463$, emotional engagement, $F(2, 146) = 73.510$, $p < .001$, partial $\eta^2 = 0.500$, metacognitive regulation, $F(2, 146) = 108.496$, $p < .001$, partial $\eta^2 = 0.596$, and academic performance, $F(2, 146) = 52.672$, $p < .001$, partial $\eta^2 = 0.417$, the Group effect remained statistically significant at posttest. The magnitude of these differences was also substantial. Partial η^2 values ranged from 0.408 to 0.596, which, in light of common benchmarks, indicate large effects [95]. The strongest effect emerged for metacognitive regulation (partial $\eta^2 = 0.596$), suggesting that a considerable proportion of the adjusted variance in posttest regulation scores was associated with group membership. Emotional engagement (partial $\eta^2 = 0.500$) and cognitive engagement (partial $\eta^2 = 0.463$) likewise showed pronounced effects, followed by academic performance (partial $\eta^2 = 0.417$) and behavioral engagement (partial $\eta^2 = 0.408$). Taken together, these findings indicate that the form of dashboard support was linked to meaningful differences across all measured outcomes, with the emotion-aware dashboard condition demonstrating the most pronounced advantages relative to the standard dashboard and control conditions.

Table 3
Multivariate test results (Pillai's trace).

Effect	Value	F	p	Partial η^2
Group	.884	11.020	< 0.001	.442

Table 4
Univariate ANCOVA results at posttest (controlling for pretest).

Dependent Variable	F(df)	p	Partial η^2	Interpretation
Behavioral Engagement	F(2, 146) = 50.653	< 0.001	.408	Large effect
Cognitive Engagement	F(2, 146) = 63.478	< 0.001	.463	Large effect
Emotional Engagement	F(2, 146) = 73.510	< 0.001	.500	Large effect
Metacognitive Regulation	F(2, 146) = 108.496	< 0.001	.596	Large effect
Academic Performance	F(2, 146) = 52.672	< 0.001	.417	Large effect

NOTE. For behavioral engagement, cognitive engagement, emotional engagement, and metacognitive regulation, the relevant pretest score was entered as the covariate. For academic performance, OQPT score was entered as the covariate. EDG = emotion-aware dashboard group; SDG = standard dashboard group; CG = control group; OQPT = Oxford Quick Placement Test.

Table 5 summarizes the Bonferroni-adjusted pairwise comparisons among the three groups at posttest for each dependent variable. A clear and consistent pattern was observed. Across all outcomes, the EDG performed significantly better than both the SDG and the CG, with all corresponding comparisons reaching statistical significance ($p < .001$). For behavioral engagement, the adjusted mean difference indicated that the EDG scored 3.62 points higher than the SDG and 8.00 points higher than the CG. The same ordering was found for cognitive engagement, where the EDG exceeded the SDG by 4.46 points and the CG by 8.58 points. Differences were most pronounced for emotional engagement, with the EDG scoring 5.40 points above the SDG and 9.74 points above the CG. The largest separation occurred for metacognitive regulation: the EDG surpassed the SDG by 17.72 points and the CG by 30.34 points. For academic performance, the EDG again showed an advantage, exceeding the SDG by 2.32 points and the CG by 4.16 points. In addition, significant differences were also observed between the SDG and the CG across all variables, indicating that access to a standard dashboard conferred measurable benefits relative to having no dashboard support. Nonetheless, the magnitude of these SDG–CG differences was consistently smaller than the corresponding EDG contrasts, which suggests added value when emotional analytics are integrated into dashboard feedback.

4.1. Learners' perceptions of the dashboard interventions

The thematic analysis of the 27 semi-structured interviews, including nine participants from each condition, yielded six overarching themes that explain how learners perceived the dashboards as supportive tools for affective awareness, progress interpretation, pacing, self-monitoring, and strategy adjustment.

Table 5
Bonferroni-adjusted pairwise comparisons at posttest.

Dependent Variable	Comparison	Mean Diff.	*p*	95% CI Lower	95% CI Upper
BE	EDG – SDG	3.62	< 0.001	1.69	5.55
BE	EDG – CG	8.00	< 0.001	6.07	9.93
BE	SDG – CG	4.38	< 0.001	2.45	6.31
CE	EDG – SDG	4.46	< 0.001	2.62	6.31
CE	EDG – CG	8.58	< 0.001	6.74	10.43
CE	SDG – CG	4.12	< 0.001	2.28	5.97
EE	EDG – SDG	5.40	< 0.001	3.45	7.35
EE	EDG – CG	9.74	< 0.001	7.79	11.69
EE	SDG – CG	4.34	< 0.001	2.39	6.29
MR	EDG – SDG	17.72	< 0.001	12.71	22.73
MR	EDG – CG	30.34	< 0.001	25.33	35.35
MR	SDG – CG	12.62	< 0.001	7.61	17.63
AP	EDG – SDG	2.32	< 0.001	1.34	3.30
AP	EDG – CG	4.16	< 0.001	3.18	5.14
AP	SDG – CG	1.84	< 0.001	0.86	2.82

NOTE. BE (Behavioral Engagement); CE (Cognitive Engagement); EE (Emotional Engagement); MR (Metacognitive Regulation); AP (Academic Performance).

Theme 1. ***Enhanced Self-Awareness through Emotional Feedback (EDG)***

EDG participants frequently described the real-time emotional indicators as a "*mirror*" that helped them see not only what they were doing on the platform, but also how they were feeling while learning. This added visibility helped learners notice changes in motivation, frustration, and boredom as they occurred and respond with concrete regulation strategies. For example, one learner explained, "*When I saw my frustration level rising, I took a break or re-read the section. It helped me stay on track*" (EDG07). Others emphasized that repeated emotional feedback helped them identify patterns across sessions. As EDG02 noted, "*I could see that my motivation usually dropped in the middle of long readings. So, I started breaking them into smaller chunks, and that made it easier to stay focused.*" Together, these accounts show how emotion-linked feedback helped learners become more aware of their affective patterns and use that awareness to regulate effort, attention, and study pacing. In this respect, the EALAD supported timely monitoring and strategic control, consistent with Winne and Hadwin's [18] and Zimmerman's [26] accounts of SRL in autonomous learning contexts.

Theme 2. ***Holistic Understanding of Learning Progress (EDG)***

A second theme concerned the integrated display of emotional analytics and clickstream indicators. EDG participants described this combination as offering a more "*complete picture*" of learning because it showed whether progress reflected focused engagement or surface-level completion. Progress metrics such as time on task and completion percentage remained useful, but emotional indicators gave learners additional context for deciding what to do next. As one participant stated, "*It showed not just my activity, but my mindset while learning*" (EDG15). This combination helped learners interpret progress as a matter of learning quality rather than completion alone. Learners reported that emotional analytics made clickstream indicators more meaningful because they could connect visible activity with concentration, readiness, and engagement quality. In this way, the EALAD helped learners decide whether continued progress reflected focused study or whether they needed to slow down, revisit content, or adjust their approach. Emotional analytics therefore helped learners interpret clickstream indicators as meaningful signs of learning quality and readiness, rather than as simple records of progress [17,73]. These accounts also align with Zimmerman's [26] view that monitoring becomes valuable when it informs control and strategy enactment.

Theme 3. ***Utility of Behavioral Metrics for Pacing (SDG)***

SDG participants generally valued the clarity of the clickstream-based dashboard. Metrics such as percentage completed, modules accessed, and time spent gave learners concrete cues for planning, pacing, and managing short-term goals. One learner reported that the dashboard helped them "*keep track of how far I'd gone and how much was left*" (SDG11), and added that "*It made me want to keep going so I could reach the next milestone*" (SDG11). For many learners, these visible progress markers created a sense of external accountability and helped them re-establish momentum after interruptions. This pattern is consistent with SRL accounts of goal setting and progress monitoring [25,26], as well as dashboard research emphasizing the role of visible feedback in learner sense-making [17,73]. **Thus, the SDG mainly supported learners by making task completion, pacing, and short-term progress more visible.**

Theme 4. ***Absence of Emotional Indicators as a Gap (SDG)***

Although SDG participants appreciated the progress indicators, many felt that the lack of emotional analytics left an important gap. The dashboard helped them maintain momentum, but it did not show whether their attention, motivation, or emotional state was supporting effective learning. Participants distinguished visible activity from meaningful engagement. As SDG04 observed, "*The numbers show if I'm active, but not if I'm in the right mindset.*" This concern reflected a broader recognition that learners can remain active in a course while confusion, fatigue, or disengagement gradually reduces learning quality. Several participants suggested that affective feedback might have helped them notice early signs of burnout or loss of focus, especially during difficult or less engaging modules. Overall, the SDG supported pacing and persistence, but it provided fewer interpretive cues for diagnosing engagement quality, a limitation also noted in dashboard research that relies heavily on descriptive behavioral data [6].

Theme 5. ***Reliance on Self-Monitoring Strategies (CG)***

In the CG, participants had to rely on their own monitoring routines because no dashboard support was available. Learners described using digital calendars, timers, handwritten notes, and checklists, but the effectiveness of these strategies depended largely on their existing self-regulation skills. One participant explained, "*I used sticky notes and my own schedule to keep going*" (CG08). For this learner, the notes served both as reminders and as a way to sustain commitment in an open-ended learning environment. The same participant added, "*Every time I finished a section, I crossed it off*" (CG08), showing how a simple checklist became a personal progress indicator. These self-created routines helped some learners impose structure on the MOOC, but they depended heavily on learners' own consistency and monitoring habits. Some reported that self-tracking became irregular, especially near deadlines, and that the lack of structured feedback made it easier for disengagement to go unnoticed. These accounts suggest that, without dashboard feedback, learners depended heavily on subjective judgments of progress and engagement, which were not always reliable.

Theme 6. ***Difficulty Recognizing Cognitive Fatigue (CG)***

A final theme in the CG concerned difficulty recognizing cognitive fatigue before it affected learning. Without dashboard feedback, several participants noticed loss of focus only after comprehension or course progress had already declined. One learner explained, "*I didn't realize I *was losing focus until I was way behind. By then, it was harder to catch up*" (CG17). Other participants described continuing to read while comprehension and retention weakened. One learner stated, "*Sometimes I kept reading, but nothing was really staying in my head. I only noticed when I tried to answer the questions and I couldn't remember the main ideas*" (CG12). Similarly, CG05 explained, "*I thought I was doing enough because I was spending time on it, but later I realized I was just going through the motions and my attention was gone*." These reflections show that time spent was sometimes mistaken for meaningful study when no external cue helped distinguish sustained attention from routine completion. Several participants suggested that even limited behavioral or affective feedback might have helped them notice fatigue earlier and take corrective action.

5. Discussion

The findings reveal a consistent pattern in the self-paced MOOC context. The EALAD was associated with substantial improvements in behavioral, cognitive, and emotional engagement, metacognitive regulation, and academic performance. The EDG showed the strongest gains across all outcomes and outperformed both the SDG and CG. This pattern suggests that dashboards become more instructionally powerful when they move beyond descriptive progress reporting and integrate emotion awareness with adaptive, regulation-oriented feedback. The results are consistent with prior evidence showing that emotion-aware and adaptive dashboards can support deeper engagement and stronger learning outcomes by responding to learners' behavioral traces and affective experiences during learning [19,96,61,21,20].

The EALAD's advantage can be understood through four connected mechanisms. First, it made learners' achievement emotions, such as confusion, frustration, boredom, and engagement, more visible before disengagement became difficult to reverse [58,97]. Second, it placed these affective indicators alongside behavioral traces, including time on task, backtracking, rapid skipping, and repeated attempts, helping learners judge whether activity reflected productive engagement or only surface persistence [98,99]. Third, it translated these cues into timely, strategy-oriented prompts, which reduced the burden learners often face when dashboards show data without clarifying what to do next. This interpretation aligns with Jivet et al. [17], who emphasized the role of dashboards in supporting sense-making and decision making, and with Giorgashvili et al. [100], who highlighted the importance of feedback specificity and personal relevance. Fourth, the EALAD supported a regulation loop by repeatedly guiding learners through monitoring, interpretation, and control, which are central processes in SRL models [25,18,26].

These mechanisms help explain the strong gains in metacognitive regulation. SRL models suggest that regulation improves when learners can identify mismatches between goals and progress, interpret the source of difficulty, and select strategies that restore productive learning [25,18,26]. In the EDG, emotionally contextualized feedback likely supported this cycle by making affective disruption visible and linking it to behavioral evidence of struggle, such as unproductive persistence or inefficient navigation [58,97]. The prompts then helped learners move from awareness to action by recommending concrete responses, including strategic rereading, use of embedded resources, restorative breaks, or effort reallocation. In a self-paced MOOC with limited teacher mediation, this shorter distance between noticing a problem and acting on it appears to be a meaningful advantage [100,17].

Control-value theory (CVT) provides a strong theoretical explanation for why the EALAD produced stronger benefits than the standard dashboard. Pekrun [7] argued that achievement emotions are shaped by learners' appraisals of control and value, and these emotions influence attention, engagement quality, strategy use, and performance [8]. In self-paced MOOCs, perceived control may weaken when tasks accumulate, comprehension breaks down, or time pressure increases. Perceived value may also decline when activities feel repetitive or disconnected from learners' goals. The EALAD likely supported control appraisals by helping learners connect negative affect to specific and changeable task conditions, such as difficulty spikes or ineffective navigation patterns, rather than interpreting these experiences as fixed ability limitations. At the same time, it may have protected perceived value by limiting prolonged boredom and frustration, which can reduce willingness to invest effort in later modules [7,8].

The engagement findings reinforce this interpretation. The EALAD was linked to gains across behavioral, cognitive, and emotional engagement, suggesting that emotion-aware feedback supported both pacing and deeper processing. This result is consistent with Han et al. [61], who found that adaptive dashboard feedback can improve participation, process quality, and learning outcomes. It also complements Fleur et al.'s [74] evidence that feedback-based dashboard designs, including those using social comparison, can strengthen motivation and academic achievement. More broadly, the present findings support the view that dashboards are more likely to sustain engagement when they provide integrated and contextualized feedback rather than progress metrics alone [98,99].

The contrast between the EDG and SDG clarifies the added value of emotion-aware feedback. Toyokawa et al. [75] showed that visualizing learning behaviors can improve study habits, which helps explain why the SDG improved relative to the CG. However, the EALAD added a distinct layer by representing the emotional quality of engagement and connecting that information to timely prompts. This interpretation is supported by the large adjusted effect for emotional engagement and is consistent with Zheng et al.'s [101] evidence that emotions are meaningfully related to SRL processes. In practical terms, the SDG helped learners monitor how much and how fast they were progressing, while the EDG also helped learners recognize how well they were studying when visible activity coincided with disengagement, confusion, or frustration. This distinction helps explain why SDG benefits were meaningful but more limited, while EDG benefits extended more strongly across engagement, regulation, and achievement.

The qualitative evidence further explains how learners used dashboard information. The SDG produced reliable gains over the CG, which supports Baker et al.'s [102] view that clickstream indicators can make study behavior more visible and manageable. Yet SDG support was mainly descriptive. It helped learners set milestones, monitor completion, manage time, and reduce procrastination, but it offered limited guidance for judging whether engagement was cognitively or emotionally productive. This pattern fits SRL accounts in which progress information supports planning and monitoring when learners have the interpretive resources needed to translate data into action [25,26]. It also supports calls for dashboards that move beyond activity tracking toward more holistic representations of learning processes [17].

By comparison, CG participants depended on unassisted self-monitoring routines, and the effectiveness of those routines varied widely. Without dashboard feedback, learners had to infer whether difficulty reflected low effort, ineffective strategy use, cognitive overload, or motivational decline, and then decide how to respond. Prior research suggests that this movement from sense-making to action is often a bottleneck in dashboard effectiveness, and that learners benefit when feedback is personalized and explicitly supports study decisions [100,17]. From this perspective, the SDG mainly supported regulation of study quantity and pace, while the EDG supported regulation of study quality, especially when negative affect made productive control more difficult. This finding reinforces Molin et al.'s [103] argument that external feedback can scaffold metacognitive development in self-paced contexts where motivational challenges are common.

Overall, the study's central contribution is that EALADs appear most effective when designed as regulation-oriented systems rather than passive visual displays. By integrating affective indicators, behavioral traces, and strategy-oriented prompts, the EALAD helped learners move from awareness to interpretation and from interpretation to action. This integrated support offers a promising direction for MOOC dashboard design, particularly in autonomous online learning environments where sustained engagement, metacognitive regulation, and timely strategy adjustment are essential for academic success.

6. Conclusions and implications

The results show that LADs, especially those providing real-time emotional feedback, can offer meaningful support for learners' metacognitive regulation, multidimensional engagement, and academic performance in a self-paced MOOC. Quantitatively, the EDG showed a consistent advantage over both the SDG and CG, with a large multivariate Group effect based on Pillai's Trace ($V = 0.884$, $p < .001$, partial $\eta^2 = 0.442$) and significant follow-up effects across all outcomes, with large adjusted effect sizes (partial $\eta^2 = 0.408$ to 0.596). The qualitative findings supported this pattern by showing that EDG participants used emotion-linked cues and behavioral traces to recognize difficulty earlier and adjust pacing and strategy use more deliberately. In contrast, SDG participants relied mainly on descriptive progress indicators, while CG participants depended on self-monitoring routines that varied in consistency and effectiveness. Overall, these findings suggest that emotion-aware feedback can reduce the distance between monitoring and control by making affective states interpretable and by helping learners decide what to do next. This interpretation aligns with SRL accounts of monitoring, interpretation, and strategic action during learning [25,18,26], as well as Jivet et al.'s [17] view that dashboards are most valuable when they support sense-making and decision making rather than progress checking alone.

The study also contributes to theory by clarifying why emotion-aware learning analytics may strengthen self-regulation and engagement in autonomous online learning. From an SRL perspective, dashboards that make learners' internal states more visible can sharpen metacognitive monitoring and support more timely metacognitive control, especially when learners must decide whether to persist, revise a strategy, or recalibrate effort [25,18,26]. Pekrun [7,46] explains that achievement emotions emerge from appraisals of control and value and then shape attention, effort, strategy use, and persistence [8]. In self-paced MOOCs, where instructor mediation is limited and learners' control and value appraisals may shift quickly, the combination of visible affective states and timely prompts appears especially useful. The findings therefore support an integrated mechanism in which affect-aware feedback increases the interpretability of learners' moment-to-moment learning states, strengthens regulation processes, sustains engagement quality, and supports performance in self-paced MOOC learning [7,25].

For MOOC designers and instructors, the findings support dashboards that go beyond descriptive progress displays. Effective EALADs should integrate affective indicators with behavioral traces and translate these combined signals into brief, actionable guidance that learners can use at the point of need [9,10,4]. This support is likely to be most helpful at moments that commonly disrupt self-paced study, such as repeated errors on comprehension checks, prolonged inactivity, rapid guessing, or recurring confusion. At these points, prompts should recommend feasible, low-burden actions, such as slowing down, revisiting prerequisite content, studying in shorter segments, using retrieval practice, or taking a short restorative break. As Susnjak et al. [4] emphasized, dashboard feedback becomes more instructionally meaningful when it helps learners move from information to concrete regulation.

The findings also have implications for dashboard usability and ethical implementation. A layered interface may reduce cognitive load by showing learners a simple emotional snapshot first, with the option to view a brief explanation that links emotional shifts to recent learning behaviors and study patterns [10]. Customizable settings, such as notification frequency and prompt type, may also help learners experience the system as supportive rather than intrusive. Because affective feedback can be misinterpreted if learners treat temporary emotions as evidence of stable ability, EALAD implementation should include a short onboarding component. Such onboarding can explain how to interpret affective signals, normalize emotional fluctuation during learning, and frame the dashboard as a tool for planning, monitoring, and post-task reflection rather than self-evaluation alone [9].

At the course level, instructors can use routine reflective check-ins to help learners connect emotional trends with strategy choices and set realistic goals for the next unit. Aggregated and privacy-protected data may also inform course improvement by identifying content segments that repeatedly lead to confusion or boredom, allowing instructors to add examples, create clarifying micro-videos, or re-sequence difficult material. Given the sensitivity of emotional data, practical adoption should be guided by transparent communication about what data are collected, why they are collected, how they are stored, and how learners can opt out. Such transparency is essential for responsible use and learner trust [77]. In the Iranian EFL MOOC context, these recommendations are particularly relevant because learners may face strong self-regulation demands and affective barriers such as anxiety, frustration, and fluctuating motivation. In such settings, emotion-aware dashboards can help sustain engagement, interrupt disengagement cycles, and support more deliberate SRL routines without adding substantial burden to instructors [78].

6.1. Limitations and future research

Several limitations should be considered when interpreting the findings. First, key outcomes, especially engagement and metacognitive regulation, were assessed mainly through self-report instruments. As Podsakoff et al. [104] noted, reliance on a single method can increase the risk of shared method variance, and self-reports may be influenced by response bias or socially desirable responding. Second, although participants were recruited from three Iranian universities, the sample remained limited to one national context, one MOOC domain, and one proficiency band. The findings are therefore most directly applicable to learners with similar linguistic and institutional profiles, and broader transferability should be examined across other proficiency levels, course types, and learning cultures [83]. Third, the emotion-aware component relied on real-time facial-expression analytics, which may be affected by recording conditions, individual differences in expressivity, and the imperfect match between observable facial cues and internally experienced emotions [62]. Fourth, the intervention did not include delayed follow-up measures, so the durability of the gains cannot be established. Finally, the feedback system used a standardized set of rules and prompts. While this supported reproducibility, it may not have fully captured individual differences in regulation needs, and it limits the extent to which the findings can separate the effects of affect visibility, prompting, and their combined operation. This distinction is important because Jivet et al. [17] emphasized that dashboard effects depend on how learners move from awareness to strategic action.

Future research should address these limitations in several ways. Studies should triangulate self-report data with behavioral traces, process measures, and brief in-situ checks of emotional experience to strengthen construct validity and reduce single-source bias. Replication studies should also include wider proficiency bands, additional age groups, more diverse institutional settings, and learners with different levels of online-learning experience and SRL profiles. Longer-term designs with delayed posttests are needed to determine whether EALADs support durable self-regulatory routines or mainly produce short-term intervention effects. Mechanism-focused research should test the proposed pathway more directly by examining whether dashboard feedback changes learners' appraisals of control and value and whether these changes predict engagement quality, strategy use, and achievement, as suggested by control-value theory and SRL models [7,46,25,18,26]. Future component experiments should also compare affect visibility alone, prompting alone, and integrated affect-plus-prompt conditions to identify which dashboard features are necessary for meaningful change. Finally, researchers should examine learners' understanding, acceptance, trust, and perceived intrusiveness of affect-aware analytics in the Iranian EFL context, since these factors are likely to shape dashboard uptake and the educational value learners derive from emotion-aware feedback.

AI use statement

The authors acknowledge that ChatGPT (OpenAI) and Grammarly were used during the manuscript preparation process solely for language editing and stylistic refinement. ChatGPT was consulted to improve clarity, sentence coherence, and academic tone, while Grammarly was used to correct grammar, punctuation, and minor formatting inconsistencies. These tools were not employed in generating research content, formulating arguments, analyzing data, or producing references. All intellectual contributions, empirical analyses, and conclusions are the exclusive work of the authors. The authors reviewed and verified all revisions and assume full responsibility for the manuscript.

Declaration of competing interest

The authors declare that there are no conflicts of interest regarding the publication of this manuscript. No financial support or any other form of funding was received for this study. The authors also confirm that there are no personal or professional relationships that could have influenced the research or its outcomes.

References

[1] Barak M, Watted A, Haick H. Motivation to learn in massive open online courses: Examining aspects of language and social engagement. Comput Educ 2016;94: 49–60. https://doi.org/10.1016/j.compedu.2015.11.010.
[2] Moore RL, Blackmon SJ. From the learner's perspective: a systematic review of MOOC learner experiences (2008–2021). Comput Educ 2022;190:104596. https://doi.org/10.1016/j.compedu.2022.104596.
[3] Chow YT, Li CH, Kang Y, Tam ES, Xiao M, Keung KL, Phua NNKT. Students' approaches to learning from physical to online environments: an assessment with exploratory factor analysis. Int J Mob Learn Organ 2024;18(3):344–62. https://doi.org/10.1504/IJMLO.2024.139773.
[4] Susnjak T, Ramaswami GS, Mathrani A. Learning analytics dashboard: a tool for providing actionable insights to learners. Int J Educ Technol High Educ 2022;19 (1):12. https://doi.org/10.1186/s41239-021-00313-7.
[5] Bodily R, Verbert K. Review of research on student-facing learning analytics dashboards and educational recommender systems. IEEE Trans Learn Technol 2017;10(4):405–18. https://doi.org/10.1109/TLT.2017.2740172.
[6] Schwendimann BA, Rodriguez-Triana MJ, Vozniuk A, Prieto LP, Boroujeni MS, Holzer A, Dillenbourg P. Perceiving learning at a glance: a systematic literature review of learning dashboard research. IEEE Trans Learn Technol 2016;10(1): 30–41. https://doi.org/10.1109/TLT.2016.2599522.
[7] Pekrun R. The control–value theory of achievement emotions: assumptions, corollaries, and implications for educational research and practice. Educ Psychol Rev 2006;18(4):315–41. https://doi.org/10.1007/s10648-006-9029-9.
[8] Pekrun R, Perry RP. Control-value theory of achievement emotions. In: Pekrun R, Linnenbrink-Garcia L, editors. International handbook of emotions in education. Routledge; 2014. p. 120–41. https://doi.org/10.4324/9780203148211-8.
[9] Banihashem SK, Noroozi O, van Ginkel S, Macfadyen LP, Biemans HJA. A systematic review of the role of learning analytics in enhancing feedback practices in higher education. Educ Res Rev 2022;37:100489. https://doi.org/10.1016/j.edurev.2022.100489.
[10] Chen J, Lin C-H, Chen G. Adolescents' self-regulated and affective learning, teacher support and digital reading literacy: a multilevel latent profile approach. Comput Educ 2023;205:104883. https://doi.org/10.1016/j.compedu.2023.104883.
[11] Picard RW. Affective computing. MIT Press; 1997.
[12] Shoumy NJ, Ang L-M, Seng KP, Rahaman DMM, Zia T. Multimodal big data affective analytics: a comprehensive survey using text, audio, visual and physiological signals. J Netw Comput Appl 2020;149:102447. https://doi.org/10.1016/j.jnca.2019.102447.
[13] Tychola KA, Vrochidou E, Papakostas G. Emotional learning analytics in education: current status, trends, and challenges. Utilizing emotional experience for best learning design practices. IGI Global; 2024. p. 479–524. https://doi.org/10.4018/979-8-3693-2663-3.ch004.
[14] Kizilcec RF, Pérez-Sanagustín M, Maldonado JJ. Self-regulated learning strategies predict learner behavior and goal attainment in massive open online courses. Comput Educ 2017;104:18–33. https://doi.org/10.1016/j.compedu.2016.10.001.
[15] Hasnine MN, Nguyen HT, Tran TTT, Bui HTT, Akçapınar G, Ueda H. A real-time learning analytics dashboard for automatic detection of online learners' affective states. Sensors 2023;23(9):4243. https://doi.org/10.3390/s23094243.
[16] Muñoz S, Sánchez E, Iglesias CA. An emotion-aware learning analytics system based on semantic task automation. Electronics 2020;9(8):1194. https://doi.org/10.3390/electronics9081194.
[17] Jivet I, Scheffel M, Schmitz M, Robbers S, Specht M, Drachsler H. From students with love: an empirical study on learner goals, self-regulated learning and sense-making of learning analytics in higher education. Internet High Educ 2020;47: 100758. https://doi.org/10.1016/j.iheduc.2020.100758.
[18] Winne PH, Hadwin A. Studying as self-regulated learning. In: Hacker DJ, Dunlosky J, editors. Metacognition in educational theory and practice. Lawrence Erlbaum Associates; 1998. p. 277–304.
[19] Aguilar SJ, Karabenick SA, Teasley SD, Baek C. Associations between learning analytics dashboard exposure and motivation and self-regulated learning. Comput Educ 2021;162:104085. https://doi.org/10.1016/j.compedu.2020.104085.
[20] Zheng J, Huang L, Li S, Lajoie SP, Chen Y, Hmelo-Silver CE. Self-regulation and emotion matter: a case study of instructor interactions with a learning analytics dashboard. Comput Educ 2021;161:104061. https://doi.org/10.1016/j.compedu.2020.104061.
[21] Valle N, Antonenko P, Valle D, Dawson K, Huggins-Manley AC, Baiser B. The influence of task-value scaffolding in a predictive learning analytics dashboard on learners' statistics anxiety, motivation, and performance. Comput Educ 2021;173: 104288. https://doi.org/10.1016/j.compedu.2021.104288.
[22] Spada M, Proctor D, Caselli G, Strodl E. Metacognition in substance misuse. In: Miller PM, editor. Principles of addiction. Principles of addiction, 1. Elsevier; 2013. p. 355–62. https://doi.org/10.1016/B978-0-12-398336-7.00037-1.
[23] Rahimi M, Katal M. Metacognitive strategies awareness and success in learning English as a foreign language: an overview. Procedia - Soc Behav Sci 2012;31: 73–81. https://doi.org/10.1016/j.sbspro.2011.12.019.
[24] Su H. An exploration of the role of metacognitive awareness and listening anxiety in EFL learners' listening comprehension. Int J List 2024;39(2):150–62. https://doi.org/10.1080/10904018.2024.2420103.
[25] Pintrich PR. A conceptual framework for assessing motivation and self-regulated learning in college students. Educ Psychol Rev 2004;16(4):385–407. https://doi.org/10.1007/s10648-004-0006-x.
[26] Zimmerman BJ. Attaining self-regulation: a social cognitive perspective. In: Boekaerts M, Pintrich PR, Zeidner M, editors. Handbook of self-regulation. Academic Press; 2000. p. 13–39.
[27] Brady M, Seli H, Rosenthal J. "Clickers" and metacognition: a quasi-experimental comparative study about metacognitive self-regulation and use of electronic feedback devices. Comput Educ 2013;65:56–63. https://doi.org/10.1016/j.compedu.2013.02.001.
[28] Kautzmann TR, Jaques PA. Effects of adaptive training on metacognitive knowledge monitoring ability in computer-based learning. Comput Educ 2019; 129:92–105. https://doi.org/10.1016/j.compedu.2018.10.017.
[29] Binali T, Tsai C-C, Chang H-Y. University students' profiles of online learning and their relation to online metacognitive regulation and internet-specific epistemic justification. Comput Educ 2021;175:104315. https://doi.org/10.1016/j.compedu.2021.104315.
[30] Sun Q, Zhang LJ, Carter S. English as a foreign language learners' metacognitive experiences and writing development: unraveling the process of learning EFL writing. Learn Individ Differ 2024;115:102540. https://doi.org/10.1016/j.lindif.2024.102540.
[31] Chigbu BI, Nekhwevha FH. High school training outcome and academic performance of first-year tertiary institution learners: taking 'input-environment-outcomes model' into account. Heliyon 2021;7(7):e07700. https://doi.org/10.1016/j.heliyon.2021.e07700.
[32] Priante A, Tsekouras D. Integrating technology in physical classrooms: the impact of game-based response systems on student learning experience. Inf Manag 2025; 62(3):104105. https://doi.org/10.1016/j.im.2025.104105.
[33] Zhao Y, Li Y, Ma S, Xu Z, Zhang B. A meta-analysis of the correlation between self-regulated learning strategies and academic performance in online and blended learning environments. Comput Educ 2025;230:105279. https://doi.org/10.1016/j.compedu.2025.105279.
[34] Mayen S, Reinhardt A, Wilhelm C. The complexities of digital media use in adolescents' learning and academic performance: an experience sampling study. Comput Educ 2025;238:105411. https://doi.org/10.1016/j.compedu.2025.105411.
[35] Wang F, Ni X, Zhang M, Zhang J. Educational digital inequality: a meta-analysis of the relationship between digital device use and academic performance in adolescents. Comput Educ 2024;213:105003. https://doi.org/10.1016/j.compedu.2024.105003.
[36] Zhang H, Wang C, Huang F, Sun D. How does mobile learning support second language learning? Evidence from CSL learners' turn construction in online communication. Int J Mob Learn Organ 2024;18(2):239–66. https://doi.org/10.1504/IJMLO.2024.137627.
[37] Yuan J, Savadatti S, Zheng G. Self-assessing a test with a possible bonus enhances low performers' academic performance. Comput Educ 2021;160:104036. https://doi.org/10.1016/j.compedu.2020.104036.
[38] Zhang R-C, Lai H-M, Cheng P-W, Chen C-P. Longitudinal effect of a computer-based graduated prompting assessment on students' academic performance. Comput Educ 2017;110:181–94. https://doi.org/10.1016/j.compedu.2017.03.016.

[39] Oga-Baldwin WLQ. Acting, thinking, feeling, making, collaborating: the engagement process in foreign language learning. System 2019;86:102128. https://doi.org/10.1016/j.system.2019.102128.
[40] Hiver P, Al-Hoorie AH, Vitta JP, Wu J. Engagement in language learning: a systematic review of 20 years of research methods and definitions. Lang Teach Res 2024;28(1):201–30. https://doi.org/10.1177/13621688211001289.
[41] Sulis G. Exploring the dynamics of engagement in the language classroom: a critical examination of methodological approaches. Res Methods Appl Linguist 2024;3(3):100162. https://doi.org/10.1016/j.rmal.2024.100162.
[42] Schiller R, Fleckenstein J, Höft L, Horbach A, Meyer J. On the role of engagement in automated feedback effectiveness: insights from keystroke logging. Comput Educ 2025;238:105386. https://doi.org/10.1016/j.compedu.2025.105386.
[43] Schiller R, Fleckenstein J, Mertens U, Horbach A, Meyer J. Understanding the effectiveness of automated feedback: using process data to uncover the role of behavioral engagement. Comput Educ 2024;223:105163. https://doi.org/10.1016/j.compedu.2024.105163.
[44] Liu Z, Tang Q, Ouyang F, Long T, Liu S. Profiling students' learning engagement in MOOC discussions to identify learning achievement: an automated configurational approach. Comput Educ 2024;219:105109. https://doi.org/10.1016/j.compedu.2024.105109.
[45] Bergdahl N. Engagement and disengagement in online learning. Comput Educ 2022;188:104561. https://doi.org/10.1016/j.compedu.2022.104561.
[46] Pekrun R. Control-value theory: from achievement emotion to a general theory of human emotions. Educ Psychol Rev 2024;36(3):83. https://doi.org/10.1007/s10648-024-09909-7.
[47] Li J, Bai B. Self-regulated learning and technological integration competency: a multilevel latent profile analysis of preschool teachers. Comput Educ 2025;232:105295. https://doi.org/10.1016/j.compedu.2025.105295.
[48] Maimaiti G, Hew KF. Gamification bolsters self-regulated learning, learning performance and reduces strategy decline in flipped classrooms: a longitudinal quasi-experiment. Comput Educ 2025;230:105278. https://doi.org/10.1016/j.compedu.2025.105278.
[49] Kaur A, Chahal KK. A learning analytics dashboard for data-driven recommendations on influences of non-cognitive factors in introductory programming. Educ Inf Technol 2024;29:9221–56. https://doi.org/10.1007/s10639-023-12125-5.
[50] Pessoa L. On the relationship between emotion and cognition. Nat Rev Neurosci 2008;9(2):148–58. https://doi.org/10.1038/nrn2317.
[51] Phelps EA. Human emotion and memory: interactions of the amygdala and hippocampal complex. Curr Opin Neurobiol 2004;14(2):198–202. https://doi.org/10.1016/j.conb.2004.03.015.
[52] Tyng CM, Amin HU, Saad MNM, Malik AS. The influences of emotion on learning and memory. Front Psychol 2017;8:1454. https://doi.org/10.3389/fpsyg.2017.01454.
[53] Flavell JH. Metacognition and cognitive monitoring: a new area of cognitive–developmental inquiry. Am Psychol 1979;34(10):906–11. https://doi.org/10.1037/0003-066X.34.10.906.
[54] Schraw G, Dennison RS. Assessing metacognitive awareness. Contemp Educ Psychol 1994;19(4):460–75. https://doi.org/10.1006/ceps.1994.1033.
[55] Scherer R, Tiemann R. Factors of problem-solving competency in a virtual chemistry environment: the role of metacognitive knowledge about strategies. Comput Educ 2012;59(4):1199–214. https://doi.org/10.1016/j.compedu.2012.05.020.
[56] Gujju K, Bandi S, Moraes M. Review of learning analytics dashboards for students. In: Daimi K, Al Sadoon A, editors. Proceedings of the third international conference on innovations in computing research (ICR'24) (lecture notes in networks and systems. 1058. Springer; 2024. p. 300–12. https://doi.org/10.1007/978-3-031-65522-7_27.
[57] Paulsen L, Lindsay E. Learning analytics dashboards are increasingly becoming about learning and not just analytics: a systematic review. Educ Inf Technol 2024;29:14279–308. https://doi.org/10.1007/s10639-023-12401-4.
[58] D'Mello S, Graesser A. Dynamics of affective states during complex learning. Learn Instr 2012;22(2):145–57. https://doi.org/10.1016/j.learninstruc.2011.10.001.
[59] Kapur M. Productive failure. Cogn Instr 2008;26(3):379–424. https://doi.org/10.1080/07370000802212669.
[60] Muis KR, Chevrier M, Singh CA. The role of epistemic emotions in personal epistemology and self-regulated learning. Educ Psychol 2018;53(3):165–84. https://doi.org/10.1080/00461520.2017.1421465.
[61] Han J, Kim KH, Rhee W, Cho YH. Learning analytics dashboards for adaptive support in face-to-face collaborative argumentation. Comput Educ 2021;163:104041. https://doi.org/10.1016/j.compedu.2020.104041.
[62] Calvo RA, D'Mello S. Affect detection: an interdisciplinary review of models, methods, and their applications. IEEE Trans Affect Comput 2010;1(1):18–37. https://doi.org/10.1109/T-AFFC.2010.1.
[63] Yadegaridehkordi E, Noor NFBM, Ayub MNB, Affal HB, Hussin NB. Affective computing in education: a systematic review and future research. Comput Educ 2019;142:103649. https://doi.org/10.1016/j.compedu.2019.103649.
[64] Moons J, De Backer C. The design and pilot evaluation of an interactive learning environment for introductory programming influenced by cognitive load theory and constructivism. Comput Educ 2013;60(1):368–84. https://doi.org/10.1016/j.compedu.2012.08.009.
[65] Paas F, Renkl A, Sweller J. Cognitive load theory and instructional design: recent developments. Educ Psychol 2003;38(1):1–4. https://doi.org/10.1207/S15326985EP3801_1.
[66] Sweller J. Cognitive load during problem solving: effects on learning. Cogn Sci 1988;12(2):257–85. https://doi.org/10.1207/s15516709cog1202_4.
[67] Hawthorne BS, Slemp GR, Vella-Brodrick DA, Hattie J. The relationship between positive and painful emotions and cognitive load during an algebra learning task. Learn Individ Differ 2025;117:102597. https://doi.org/10.1016/j.lindif.2024.102597.
[68] Wijnands A, van Rijt J, Stoel G, Coppen P-A. Balancing between uncertainty and control: teaching reflective thinking about language in the classroom. Linguist Educ 2022;71:101087. https://doi.org/10.1016/j.linged.2022.101087.
[69] Bandhu D, Mohan M, Nittala NAP, Jadhav P, Bhadauria A, Saxena KK. Theories of motivation: a comprehensive analysis of human behavior drivers. Acta Psychol 2024;244:104177. https://doi.org/10.1016/j.actpsy.2024.104177.
[70] Chiu TK, Falloon G, Song Y, Wong VW, Zhao L, Ismailov M. A self-determination theory approach to teacher digital competence development. Comput Educ 2024;214:105017. https://doi.org/10.1016/j.compedu.2024.105017.
[71] Deci EL, Ryan RM. Intrinsic motivation and self-determination in human behavior. Plenum; 1985.
[72] Jeno LM, Vandvik V, Eliassen S, Grytnes J-A. Testing the novelty effect of an m-learning tool on internalization and achievement: a self-determination theory approach. Comput Educ 2019;128:398–413. https://doi.org/10.1016/j.compedu.2018.10.008.
[73] Verbert K, Govaerts S, Duval E, Santos JL, Van Assche F, Parra G, Klerkx J. Learning dashboards: an overview and future research opportunities. Pers Ubiquitous Comput 2014;18(6):1499–514. https://doi.org/10.1007/s00779-013-0751-2.
[74] Fleur DS, van den Bos W, Bredeweg B. Social comparison in learning analytics dashboard supporting motivation and academic achievement. Comput Educ Open 2023;4:100130. https://doi.org/10.1016/j.caeo.2023.100130.
[75] Toyokawa Y, Majumdar R, Kondo T, Horikoshi I, Ogata H. Active reading dashboard in a learning analytics–enhanced language-learning environment: effects on learning behavior and performance. J Comput Educ 2024;11:495–522. https://doi.org/10.1007/s40692-023-00267-x.
[76] Geng X, Yamada M. The role of dashboards in augmented-reality-based language learning: enhancing language learning and metacognitive awareness. SAGE Open 2025;15(2):21582440251341675. https://doi.org/10.1177/21582440251341675.
[77] Ahmadi Safa M, Lotfi J. Iranian EFL learners' online self-regulated learning, use of communication strategies, test anxiety and online speaking test performance: a structural equation modeling approach. Int J Lang Test 2025;15(1):173–92. https://doi.org/10.22034/ijlt.2024.466895.1361.
[78] Pan H, Xia F, Kumar T, Li X, Shamsy A. Massive open online course versus flipped instruction: impacts on foreign language speaking anxiety, foreign language learning motivation, and learning attitude. Front Psychol 2022;13:833616. https://doi.org/10.3389/fpsyg.2022.833616.
[79] Cohen J. Statistical power analysis. Curr Dir Psychol Sci 1992;1(3):98–101. https://doi.org/10.1111/1467-8721.ep10768783.
[80] Faul F, Erdfelder E, Buchner A, Lang AG. Statistical power analyses using G* power 3.1: tests for correlation and regression analyses. Behav Res Methods 2009;41(4):1149–60. https://doi.org/10.3758/BRM.41.4.1149.
[81] Lakens D. Sample size justification. Collabra: Psychol 2022;8(1):33267. https://doi.org/10.1525/collabra.33267.
[82] Bornstein MH, Jager J, Putnick DL. Sampling in developmental science: Situations, shortcomings, solutions, and standards. Dev Rev 2013;33(4):357–70. https://doi.org/10.1016/j.dr.2013.08.003.
[83] Henrich J, Heine SJ, Norenzayan A. The weirdest people in the world? Behav Brain Sci 2010;33(2–3):61–83. https://doi.org/10.1017/S0140525X0999152X.
[84] Al-Obaydi LH, Shakki F, Tawafak RM, Pikhart M, Ugla RL. What i know, what i want to know, what i learned: activating EFL college students' cognitive, behavioral, and emotional engagement through structured feedback in an online environment. Front Psychol 2023;13:1083673. https://doi.org/10.3389/fpsyg.2022.1083673.
[85] Fredricks JA, Blumenfeld PC, Paris AH. School engagement: potential of the concept, state of the evidence. Rev Educ Res 2004;74(1):59–109. https://doi.org/10.3102/00346543074001059.
[86] Greene JA, Azevedo R. The measurement of learners' self-regulated cognitive and metacognitive processes while using computer-based learning environments. Educ Psychol 2010;45(4):203–9. https://doi.org/10.1080/00461520.2010.515935.
[87] Rovers SFE, Clarebout G, Savelberg HHCM, de Bruin ABH, van Merriënboer JJG. Granularity matters: comparing different ways of measuring self-regulated learning. Metacognition Learn 2019;14:1–19. https://doi.org/10.1007/s11409-019-09188-6.
[88] Winne PH. Improving measurements of self-regulated learning. Educ Psychol 2010;45(4):267–76. https://doi.org/10.1080/00461520.2010.517150.
[89] Palinkas LA, Horwitz SM, Green CA, Wisdom JP, Duan N, Hoagwood K. Purposeful sampling for qualitative data collection and analysis in mixed method implementation research. Adm Policy Ment Health Ment Health Serv Res 2015;42(5):533–44. https://doi.org/10.1007/s10488-013-0528-y.
[90] Hoffmann TC, Glasziou PP, Boutron I, Milne R, Perera R, Moher D, Altman DG, Barbour V, Macdonald H, Johnston M, Lamb SE, Dixon-Woods M, McCulloch P, Wyatt JC, Chan AW, Michie S. Better reporting of interventions: template for intervention description and replication (TIDieR) checklist and guide. BMJ 2014;348:g1687. https://doi.org/10.1136/bmj.g1687.
[91] Appelbaum M, Cooper H, Kline RB, Mayo-Wilson E, Nezu AM, Rao SM. Journal article reporting standards for quantitative research in psychology: the APA

publications and communications board task force report. Am Psychol 2018;73 (1):3–25. https://doi.org/10.1037/amp0000191.
[92] Wilkinson L. Statistical methods in psychology journals: guidelines and explanations. Am Psychol 1999;54(8):594. https://doi.org/10.1037/0003-066X.54.8.594.
[93] Cumming G. The new statistics: why and how. Psychol Sci 2014;25(1):7–29. https://doi.org/10.1177/0956797613504966.
[94] Braun V, Clarke V. Using thematic analysis in psychology. Qual Res Psychol 2006; 3(2):77–101. https://doi.org/10.1191/1478088706qp063oa.
[95] Cohen J. Statistical power analysis for the behavioral sciences. 2nd ed. Lawrence Erlbaum Associates; 1988.
[96] de Vreugd L, van Leeuwen A, van der Schaaf M. Students' use of a learning analytics dashboard and influence of reference frames: goal setting, motivation, and performance. J Comput Assist Learn 2025;41(2):e70015. https://doi.org/10.1111/jcal.70015.
[97] Harley JM, Lajoie SP, Frasson C, Hall NC. Developing emotion-aware, advanced learning technologies: a taxonomy of approaches and features. Int J Artif Intell Educ 2017;27(2):268–97. https://doi.org/10.1007/s40593-016-0126-8.
[98] Jivet I, Scheffel M, Specht M, Drachsler H. License to evaluate: preparing learning analytics dashboards for educational practice. In: Proceedings of the 8th international conference on learning analytics and knowledge (LAK '18). Association for Computing Machinery; 2018. p. 31–40. https://doi.org/10.1145/3170358.3170421.
[99] Matcha W, Uzir NA, Gašević D, Pardo A. A systematic review of empirical studies on learning analytics dashboards: a self-regulated learning perspective. IEEE Trans Learn Technol 2020;13(2):226–45. https://doi.org/10.1109/TLT.2019.2916802.
[100] Giorgashvili T, Jivet I, Artelt C, Biedermann D, Bengs D, Goldhammer F, Drachsler H. From reflection to action: a controlled field study on how learners interpret and respond to feedback in learning analytics dashboards. J Comput Assist Learn 2025;41(4):e70073. https://doi.org/10.1111/jcal.70073.
[101] Zheng J, Lajoie S, Li S. Emotions in self-regulated learning: a critical literature review and meta-analysis. Front Psychol 2023;14:1137010. https://doi.org/10.3389/fpsyg.2023.1137010.
[102] Baker R, Di X, Park J, Yu R, Li Q, Cung B, Fischer C, Rodriguez F, Warschauer M, Smyth P. The benefits and caveats of using clickstream data to understand student self-regulatory behaviors: opening the black box of learning processes. Int J Educ Technol High Educ 2020;17:13. https://doi.org/10.1186/s41239-020-00187-1.
[103] Molin F, Haelermans C, Cabus S, Groot W. The effect of feedback on metacognition: a randomized experiment using polling technology. Comput Educ 2020;152:103885. https://doi.org/10.1016/j.compedu.2020.103885.
[104] Podsakoff PM, MacKenzie SB, Lee JY, Podsakoff NP. Common method biases in behavioral research: a critical review of the literature and recommended remedies. J Appl Psychol 2003;88(5):879–903.

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