Technology Assisted Language Education TALE

Volume 2. Issue 4. December 2024. Pages 1 to 21

https://doi.org/10.22126/tale.2024.11178.1065 Document Type: Research Paper

Enhancing Students' Online Self-Regulation through Learning Analytics: Students' Expectations

Maryam Alibeigi[1], Mohammad Davoudi[2], Saeed Ghaniabadi[3], Seyyed Mohammad Reza Amirian[4]

[1]Ph.D. Department of English Teaching and Literature, Faculty of Humanities, Hakim Sabzevari University, Sabzevar, Iran.. Maryam.Alibeigi1991@gmail.com

[2]Associate Professor, Department of English Teaching and Literature, Faculty of Humanities, Hakim Sabzevari University, Sabzevar, Iran. Davoudi2100@gmail.com

[3]Assistant Professor, Department of English Teaching and Literature, Faculty of Humanities, Hakim Sabzevari University, Sabzevar, Iran. sghaniabadi@yahoo.com

[4]Associate Professor, Department of English Teaching and Literature, Faculty of Humanities, Hakim Sabzevari University, Sabzevar, Iran. smr.amirian@gmail.com

Received October 02, 2024**; Accepted:** December 08, 2024

Abstract

This study aimed to enhance the online self-regulation skills of TEFL students by incorporating insights from highly self-regulated learners—a significantly informative yet neglected cohort in LA literature—into the design of Learning Analytics (LA) to promote effective online self-regulated learning (SRL). Current LA research often emphasises technical aspects over pedagogical insights. To address this gap, we included three distinctive features to move beyond the current literature: a pedagogical lens, a retrospective design with a pragmatism framework for interpreting the results, and the purposive sampling of highly self-regulated students. Semi-structured interviews and reflective journals were used as the instruments, and a thematic analysis was conducted on the data through Nvivo. The analysis yielded three main themes: technology integration and dashboard customisation, human intervention and collaboration, personalised learning, feedback, and recommendations. The findings highlight implications for educational practices, policies, and LA design, emphasising the need to view students as active, research-oriented participants.

Keywords: Learning Analytics, Self-regulation, Students' Expectations, Online Learning

*Corresponding Author: Mohammad Davoudi.

Email: Davoudi2100@gmail.com

Introduction

The transition to online education, hastened by the pandemic, has highlighted its challenges and potential in higher education. This increased focus on digital learning has led to a global effort to find innovative solutions (Crawford et al., 2020). Effective self-regulation is crucial to educational achievement, with its absence linked to poor academic results (e.g., Simonson et al., 2019). The unique challenges of online learning, such as limited face-to-face interaction and structural limitations, necessitate the development of self-regulation skills to maintain learner motivation and accountability (Hensley et al., 2022). Therefore, the criticality of online SRL competencies and students' poor online SRL skills necessitates thoroughly exploring technological affordances to bolster SRL (Pedrotti & Nistor, 2019).

Contemporary research focuses on technology's role in advancing students' SRL skills. Digital platforms are recommended for supporting the SRL cycle—planning, action, and reflection—to improve cognitive awareness (Bartolomé & Steffens, 2011). Metacognition is crucial in SRL, connecting motivational and executive learning aspects (Pilling-Cormick & Garrison, 2007). In this sense, LA enhances metacognitive skills by providing real-time feedback on learners' activities. Although LA informs pedagogical approaches (Knight et al., 2013), learners' expectations of LA remain under-researched (Schumacher & Ifenthaler, 2018).

Learning analytics systems (McLoughlin & Lee, 2010) exemplify technology's contribution to student self-regulation. These systems provide web-based dashboards with customisable control panels displaying personalised learning features adaptable to real-time learning processes (Park & Jo, 2015). LA facilitates the analysis and modification of learning behaviours through various tools such as recommendations, visualisations, and self-assessments (Ifenthaler & Widanapathirana, 2014), thereby enhancing students' abilities to plan, monitor, and reflect on their learning (McLoughlin & Lee, 2010).

SRL is a mandatory skill in online education, and without it, students would fail to achieve their full academic potential (Simonson et al., 2019), with LA being pivotal in online SRL skill enhancement. However, on the one hand, research on LA mainly emphasises its technical features in controlled settings and largely overlooks its pedagogical aspects (Gašević et al., 2015). On the other hand, successful design and implementation of learning analytics systems could fail if learners' expectations are not carefully examined (Deci et al., 1996). Therefore, exploiting the student's expectations of learning analytics systems through the pedagogical lens of self-regulation warrants closer scrutiny. Furthermore, to our knowledge, no study has investigated highly self-regulated learners' perspectives on what LA can offer to enhance SRL. In the present study, we aim to pivot scrutiny towards highly self-regulated learners' expectations of LA as an invaluable source of information on improving SRL to fill this gap.

Volume 2. Issue 4. December 2024. Pages 1 to 21

The present research also extends beyond the current literature by incorporating unique elements such as the purposive sampling of highly self-regulated learners, adopting a retrospective design, and integrating an SRL pedagogical lens. Therefore, the following critical research question has been formed:

> How does learning analytics (LA) promote self-regulated learning (SRL) skills from the perspective of self-regulated students?

Literature Review

The heightened significance of online education underscores the importance of examining the challenges in this domain, especially in the context of increased reliance on virtual learning environments (Paudel, 2021). The many advantages of online education, including flexibility and convenience, have made E-learning an increasingly popular option for students (Rajeh et al., 2021). However, a significant remaining challenge to education is that students fail to self-regulate their learning endeavours in E-learning environments (Pedrotti & Nistor, 2019). Meanwhile, few would refuse to acknowledge the significance of SRL skills in online education (Vishwakarma & Tyagi, 2022).

Self-regulation is a core conceptual framework for comprehending the cognitive, metacognitive, and motivational dimensions of learning (Pintrich et al., 1993). Scholarly inquiries reveal a paradox wherein students, despite SRL's recognised importance and benefits, frequently exhibit deficient SRL competencies in online learning environments (e.g., Vishwakarma & Tyagi, 2022). To mitigate this discrepancy, the strategic deployment of technology, mainly through LA, emerges as a pivotal mechanism for fostering SRL within online educational frameworks. Empirical evidence suggests that LA can significantly enhance learners' SRL capabilities and academic performance (Zheng et al., 2023).

LA systematically analyses big data to refine educational processes (Brown, 2012). It predominantly harnesses data from student information systems and learning management systems to apply analytical techniques such as prediction, clustering, and relationship mining, which support informed decision-making (Romero & Ventura, 2010; Siemens & Baker, 2012). The effectiveness of LA in discerning student behaviour and bolstering retention (Zhen et al., 2023), as well as in enhancing SRL skills (Siemens & Long, 2011), is contingent upon a deep understanding of stakeholder expectations (Deci et al., 1996).

Contemporary research has scrutinised the expectations of various stakeholders from LA, predominantly focusing on learners (e.g., Roberts et al., 2016; Schumacher & Ifenthaler, 2018; Whitelock-Wainwright et al., 2019). Instruments such as questionnaires, interviews (e.g., Schumacher & Ifenthaler, 2018), and focus groups have been employed to gauge students' expectations (e.g., Tsai et al., 2020). Notably, Schumacher and Ifenthaler (2018) highlighted students' preference for LA features that facilitate reminders, content revision, self-evaluation, assignment assessment, and strategic learning guidance for successful course completion.

Moreover, Tsai et al. (2020) underscored students' anticipation of consent for using their identifiable data in LA. They also envisaged enhanced educational services and aspired to enhance academic services, including pedagogy, personalised support, and resource allocation, alongside a desire for the university's comprehensive elevation relative to its counterparts. However, another study on students' perception of LA revealed six themes: uninformed and uncertain, personalisation, driving inequality, privacy concerns, impeding independence, help, or hindrance (Roberts et al., 2016).

Additionally, other studies have highlighted the emerging expectations among students from LA, including privacy concerns (Arnold & Sclater, 2017; Jones et al., 2020) and personalised and adaptive learning opportunities (Tapalova & Zhiyenbayeva, 2022). Furthermore, user-friendliness (Bahari et al.), collaborative learning experiences (Wise et al., 2021), and the predictive capability of LA (Kurni et al., 2023) are the most recurring themes in the LA literature.

As the literature review suggests, it would be wrong to claim that no studies explore the stakeholders' expectations of LA. However, to our knowledge, very few studies have viewed LA from the pedagogical lens of SRL. Furthermore, to our knowledge, no study has explored highly self-regulated learners' perspectives on what LA can offer to improve online self-regulation skills. In the current study, we aim to shift attention toward highly self-regulated learners' expectations of LA as an invaluable source of information on boosting SRL to fill this gap. Moreover, the present study moves beyond the current literature by encompassing the distinctive features of the purposive sampling of highly self-regulated learners, deploying a retrospective design, and including an SRL pedagogical lens. Therefore, the current study also attempts to answer the vital question of how LA can enhance online SRL from the perspective of a neglected but highly informative group of learners.

Method

Context

Iranian higher education system is governed by the Ministry of Science, Research, and Technology for non-medical universities and the Ministry of Health and Medical Education for medical schools. The system reflects a mix of old and new educational values. It has evolved significantly, echoing the shifting political climate of the country. The design and execution of academic policies are swayed by these changes, affecting how education is delivered (Jafari, 2024). While the student body is varied, educational access is uneven, with rural students facing hurdles. The Islamic Azad University is one initiative trying to improve this situation. Overall, the system is actively adapting,

Volume 2. Issue 4. December 2024. Pages 1 to 21

balancing the push for modernisation with the need to stay true to its cultural roots, showcasing the complex educational reform process.

Participants

The participants consisted of undergraduates of applied linguistics enrolled in different universities in Iran who had experienced online education during the two years due to the coronavirus pandemic. The participants were recruited from online social networks, including Academia and LinkedIn. They included both male and female Persian speakers ranging in age from 20 to 24. Of an initial cohort of 100 persons, 12 participants were selected based on their performance on the Quick Placement Test (QPT) and Online Self-regulation Learning Questionnaire (OSLQ). The scores of the selectees fell 48 or above in QPT (advanced to very advanced proficiency) and 90 or above on OSLQ (highly self-regulated) based on purposive and criterion sampling procedures. Furthermore, their documented average grade point was 18 or above in the university TEFL program.

The rationale for the sample size was based on the data saturation technique and Creswell& Poth's (2013) guidelines, recommending 3 to 15 participants. This ensured comprehensive and representative data. Data saturation confirmed the sample's adequacy when no new themes emerged from the data collection procedure. Furthermore, the participants were informed about the study's aim and procedure. They were also notified that their participation was voluntary, and anonymity was ensured.

Instruments

Descriptions of the data collection instruments are presented below

Quick Placement Test (QPT)

QPT was administered to all the participants to gauge their language achievement. The version of the QPT used in this study contained 60 items, all in the multiple-choice format, and was divided into two parts: part one (questions 1–40) and part two (questions 41–60). The participants completed the test within 30 minutes. The ranking is as follows: 1-17 Beginner, 18-27 Elementary, 28-36 Lower-intermediate, 37-47 Upper-intermediate, 48-55 Advanced, 56-60 Very advanced (Syndicate, 2001).

Online Self-regulation Learning Questionnaire (OSLQ)

The online Self-regulated Questionnaire (OSLQ) is a 24-item scale with a 5-point Likert response format with values ranging from strongly agree (5) to strongly disagree (1). Higher scores on this scale indicate higher levels of self-regulation in online learning courses. The OSLQ scale encompasses six constructs with subscales of goal setting, task strategies, environment structuring, time management, help-seeking, and self-evaluation. Nunnally (1978) suggested that the acceptable reliability score is .70 or better in basic social sciences. The OSLQ in the present study achieved an acceptable reliability score of .91, as indicated by the Cronbach alpha coefficient.

Guided Reflective Journal

Researchers developed a reflective journal guided by Gibbs' reflective cycle (1988), a six-stage model for scrutinising experiences. This framework aids in systematically reflecting on one's experiences through six different stages: Description of the experience, feelings and thoughts about the experience, evaluation of the experience (both good and bad), analysis to make sense of the situation, and conclusion about what you learned, and what you could have done differently. Students were allotted two weeks to complete this journal, allowing ample time for recollection and reflection. Please refer to the data analysis section for a detailed explanation of credibility, confirmability, dependability, and transferability.

Interview

Researchers conducted semi-structured interviews with open-ended questions to ensure a deeper understanding of the cognitive, metacognitive, and motivational aspects of students' self-regulation strategies in online learning and their expectations for LA to bolster these strategies. The interview design drew upon Zimmerman's (2000) cyclical phases model and existing LA literature. Careful piloting, training of the interviewer, and inter-rater reliability in the coding of the responses were carried out to ensure reliability (Silverman, 2013). To validate the interview measure, the researchers controlled for sources of bias. Sources of bias include the interviewer, the interviewee, and the substantive content of the questions (Ary et al., 2018). Detailed explanations of credibility, confirmability, dependability, and transferability can be found in the trustworthiness section.

Procedures

Initially, Invitations were sent based on Academia and LinkedIn profiles to streamline access to a broader range of relevant participants, accelerating the process to meet purposive and criterion sampling requirements. The invitation letter included information about the characteristics of our participants, the purpose, procedure, and ethics of the study, and a reward for their participation. If the invitee accepted our request to participate in our research project, a consent form was presented to them to be signed right before the actual initiation of the project. Upon receiving the consent form for their participation, they were asked to complete a version of the QPT and the OSLQ for the study's first phase. Next, they were asked to report their documented university grade point average in their TEFL program.

After analysing the results, twelve participants whose scores were between 48-60 advanced to a very advanced level of English language proficiency) in QPT and a

Volume 2. Issue 4. December 2024. Pages 1 to 21

score of 90 or above on OSLQ (high level of self-regulation) with an 18 or above GPA were selected based on the criterion and purposive sampling for the next phase of the study. Next, the participants were asked to fill out a guided reflective journal based on Gibbs' reflective model (1988) about their self-regulation strategies during their online courses for their mandatory online education during the pandemic. Since the reflective journal was based on a retrospective approach, the participants were given two weeks before they submitted their guided reflective journals. It provided them with sufficient time to recall their experiences. Finally, they were interviewed on how their online self-regulation strategy formed their expectation of LA in boosting their SRL practices. Before the interview, both Zimmermans' cyclical model of self-regulation and LA were introduced. They were asked to think about how LA could enhance their self-regulation experience on an online platform. The interview took 40 minutes to 1 hour, with a 10-minute break between each section. Next, the researchers employed an inductive thematic analysis with coding reliability, using a codebook and multiple coders to ensure objectivity and minimise researcher bias (Braun & Clarke, 2021).

Data analysis

The study initially used ISO-certified Voxtab transcription, trusted by major organisations (Aniedu et al., 2020), followed by thematic content analysis to identify dominant patterns(Creswell & Poth, 2013). The thematic analysis followed the structured approach proposed by Braun and Clarke (2006), involving six iterative phases: familiarising with the data, generating initial codes, searching for themes, reviewing themes, defining and naming themes, and producing the final report. This systematic process allowed for a rigorous, in-depth exploration of participant responses, ensuring that the themes derived were data-driven and closely aligned with the study's objectives. For instance, the Technology Integration and Dashboard Customization theme emerged from participants' frequent references to integrating various apps, including time-management tools, self-recording options, AI-powered tools, educational sites, customisable dashboards, and diverse feedback mechanisms. This reflected a shared experience of a need for enhanced technological tools to improve efficacy, goal-orientedness, and reflective practices, a sentiment consistently echoed by multiple participants. Another theme, human intervention and collaboration was identified by categorising responses related to personalised human feedback, support, and collaboration. Here, the participants frequently emphasised incorporating human elements like human feedback, personalised tutoring systems, educational advisory support, and multimodal collaborative tools to enhance the learning experience and foster student community and collaboration. Finally, the theme of Personalized Learning, Feedback, and Recommendation Systems was derived by integrating categories related to adaptive learning systems, motivational and reflectional prompts, real-time and delayed feedback, personalised recommendations, self-assessment tools, and matching compatible study partners. This theme highlighted participants' appreciation for tailored feedback and self-assessment tools.

These three principal themes emerged through this iterative coding, categorising, and refining process, grounded in the participants' input and directly aligned with the study's research objectives. Furthermore, NVivo 10, a trusted qualitative data analysis tool, ensured profound insight discovery and data interpretation (Ritchie et al., 2013).

Semi-structured interviews and reflective journals were developed based on Zimmerman's SRL model (2000) and a literature review to ensure trustworthiness. Expert validation was obtained, followed by piloting. Participants were encouraged to engage authentically, with confidentiality assured. Interviewers received training to establish rapport and maintain neutrality throughout the process.

The credibility and confirmability of the findings were established through member checks (Birth et al., 2016) and debriefing (Silverman, 2013). Three PhD researchers familiar with thematic analysis and the research topic under investigation were involved as coders to ensure dependability and minimise bias. The inter-coder agreement was assessed by comparing the coded dataset among the three coders, yielding a high percentage of agreement (95%), which indicates a substantial level of consistency and suggests that the coding framework used in the analysis was well-defined (Campbell et al., 2013). The remaining 5% disagreement rate likely reflects differences in interpretation or subjective judgment, which is common in qualitative data analysis (Creswell & Poth, 2013). Furthermore, transferability was supported by detailing the participants' characteristics, the study contexts, and verbatim excerpts to illustrate key themes, allowing readers to assess the applicability of the findings to other settings and populations (Palinkas et al., 2015). Collectively, these measures contribute to the overall trustworthiness of the study's findings.

Results

In the present study, researchers aim to elicit highly self-regulated students' perspectives on how LA could enhance their self-regulation experiences in an online learning environment. In other words, by employing a comprehensive approach to our data collection and analysis, we aimed to provide rich insights into highly self-regulated students' expectations of LA in the context of online learning within the field of TEFL. The following three themes emerged from the current study.

Technology Integration and Dashboard Customization

The theme "Technology Integration and Dashboard Customization in Learning Analytics" reflects participants' expectations regarding integrating diverse technological tools and customising LA platforms to improve learner experience and learning support. The excerpts highlight the desire to integrate various apps, AI-

Volume 2. Issue 4. December 2024. Pages 1 to 21

powered tools, and educational sites within the LA framework to provide users with flexibility, autonomy, choice, and access to various resources. Additionally, the emphasis on time-management tools, self-recording options, customisable dashboards, and diverse feedback mechanisms underscores the participants' recognition of the importance of personalised and adaptive features in LA to support SRL. Below, a series of relevant excerpts to the current theme are presented:

Stella: "I think LA should include other apps like to-do lists, mind maps, Telegram, and other applications enabling us to generate the learning behaviour data we feel comfortable with in any forum, leading to increased user-friendliness and convenience."

Ethan: "I believe that LA should be integrated with LMS, utilising AI-powered tools such as chatbots. Including diverse chatbots enables us to pose numerous inquiries at any given time. Moreover, it would assist in overcoming our hesitancy to ask fundamental questions that we may assume common knowledge but are unfamiliar to us. This integration would enhance our confidence and alleviate the stress and anxiety that often arise from a lack of understanding in our learning endeavours."

Evelyn: "I think LA should allow us to add other sites such as YouTube and more educational sites into our accounts as add-ins to ensure access to a wide range of relevant information."

Audrey: "Time-management tools and self-recording options are among the most important features that must be included in LA. Smart and fast time management is required for exercising SRL behaviour like time management and reviewing and reflecting on our learning process."

Savannah: "I believe that a must-have feature for LA is customisable dashboards, through which we can choose the feedback type we want to receive, for instance, visual, qualitative, or quantitative. It increases our feedback choices and obviates feedback overload."

The theme of "Technology Integration and Dashboard Customization in Learning Analytics" aligns with research on the fusion of AI with LA to foster personalised and adaptive educational settings (Sajja et al., 2023). The advocacy for incorporating AI utilities, chatbots, and customisable dashboards echoes the literature on AI-driven adaptive learning platforms that offer tailored support, personalised feedback, and extensive resources, enriching the SRL journey (Zawacki-Richter et al., 2019).

Moreover, this theme intersects with the literature highlighting the value of customisation and diverse feedback mechanisms in LA platforms (Chen et al., 2020; Chang et al., 2023). Furthermore, the students' emphasis on user-centred design and personalised learning echoes the importance of user-friendly interfaces and providing qualitative and quantitative feedback (Nouri et al., 2019). The expectation of technology integration underscores the potential for AI to further support SRL practices in online settings (Hamshin et al., 2023).

Human Intervention and Collaboration.

The human intervention and collaboration theme underscores the significance of incorporating human-centric support and collaborative learning experiences within the LA framework (Roll & Winne, 2015). Participants advocate for including human feedback, personalised tutoring systems, educational advisory support, and multimodal collaborative tools to enhance the learning experience and foster student community and collaboration (Alfredo et al., 2023). The following is a selection of student excerpts pertinent to the present theme:

Abigail: "While automatic feedback generated by LA is useful, it does not fully meet the need for feedback. Therefore, I propose that LA include a collaboration tool allowing teachers and peers to provide feedback. Furthermore, human feedback is more meaningful and pedagogically informed for students."

Madison: "We need objective and subjective feedback from instructors or peers."

Chloe: "I think LA must implement human tutoring systems to let students search for tutors through some filtering features, allowing students to find expert tutors in specific areas where they are struggling."

Nathan: Students should have a platform to engage in reciprocal peer tutoring sessions to exchange knowledge with their peers."

Penelope: "LA needs to include an educational advisory system. This system would allow learners to consult with teachers, peers, or educational advisors for their learning plans, strategies, materials, techniques, and tools."

Sophia: "LA should incorporate multimodal collaborative learning tools. These tools facilitate communication and convey information appropriately for learners, allowing them to exercise choice over the input-receiving and output-sharing modalities."

This theme aligns with current literature emphasising the potential of AI-powered tools to complement, rather than replace human expertise in providing meaningful feedback, personalised support, and collaborative learning experiences (Alfredo et al., 2023; Tapalova & Zhiyenbayeva, 2022). The participants' emphasis on the value of human feedback underscores the importance of human-centred pedagogy and personalised learning experiences (Baker & Siemens, 2014).

Furthermore, the participants' suggestions for integrating human tutoring systems, educational advisory support, and multimodal collaborative tools align with the goals of AI-enhanced educational platforms, collaborative learning, and access to diverse resources to optimise their learning experiences (Ifenthaler & Widanapathirana,

Volume 2. Issue 4. December 2024. Pages 1 to 21

2014). This integration also highlights the relevance of the participants' expectations for human-centred feedback (Baker & Siemens, 2014).

Personalised learning, feedback, and recommendation systems

The "Personalised Learning, Feedback, and Recommendation Systems" theme reflects participants' expectations for LA to provide adaptive support, personalised feedback, and customised learning recommendations (Sedrakyan et al., 2020). The excerpts highlight the participants' emphasis on adaptive learning systems, motivational and reflectional prompts, real-time and delayed feedback, personalised recommendations, self-assessment tools, and matching compatible study partners. These expectations underscore the participants' desire for educational services that cater to their individual learning needs, preferences, and SRL practices (Shemshack et al., 2019). Some relevant excerpts to the current theme are presented below:

Levi: "To maximise SRL support, LA should offer adaptive systems that consider learners' recent knowledge status for more accurate guidance."

Stella: "In my opinion, various prompts like motivators, guided reflection, and reminders must be incorporated into LA."

Penelope: "The LA system must encompass both real-time AI-powered feedback and chatbots for further inquiry into the feedback. Furthermore, delayed instructor or peer feedback can provide a deeper understanding of the subject."

Savannah: "LA must provide real-time feedback, including recommendations for learning materials and links to explanatory videos."

Evelyn: "I believe that self-assessment tools with self-correction options for tests and plans improve our chances for self-monitoring and reflection. In essence, not only should we be able to revise our tests and tasks, but we should also be able to create revision plans."

Nathan: "I think that LA should pair the most compatible study partners by thoroughly analysing the learners' profiles and suggesting suitable study partners or groups based on their learning needs, wants, and preferences."

Sophia: "I believe the LA human tutoring system should include some built-in features to match our profiles with a list of tutors and peers separately. These recommendation systems can help us as we seek tutors or study partners."

This theme aligns with the current literature emphasising the potential of adaptive learning systems, personalised feedback, and recommendation engines to support students' self-regulation (Digel et al., 2023; George & Wooden, 2023; Selwyn, 2019). The participants' expectations for adaptive learning systems, personalised prompts, real-time and delayed feedback, and self-assessment tools resonate with the literature on AI-driven customised learning environments (Baker & Siemens, 2014; Majid & Lakshmi, 2020), which aims to provide adaptive feedback, and personalised recommendations to optimise students' SRL practices (D'Mello & Graesser, 2012).

The findings also underscore the potential for AI-driven educational technologies to facilitate students' personalised learning, adaptive feedback, and tailored support (Gašević et al., 2015). The participants' expectations for personalised learning, feedback, and recommendation systems align with the goals of AI-enhanced educational platforms, which aim to empower students to engage in personalised and adaptive learning, receive tailored feedback, and access customised learning recommendations to optimise their online self-regulation (Ifenthaler & Widanapathirana, 2014; Tapalova & Zhiyenbayeva, 2022).

Discussion

The qualitative research findings reveal insightful perspectives on the expectations of highly self-regulated students regarding enhancing SRL through LA. The thematic analysis highlights three critical areas of focus: technology integration and dashboard customisation, human intervention and collaboration, and personalised learning, feedback, and recommendation systems.

The emphasis on technology integration and dashboard customisation reflects an acknowledgement of LA's potential to cater to diverse learning styles, cognitive preferences, learner autonomy, and students' voices. These notions align with the Control-Value Theory of Achievement Emotions, which posits that perceived control positively influences emotions in academic settings (Pekrun, 2006). Ultimately, emotion enhancement culminates in heightened engagement (Fredricks et al., 2004) and elevated motivation (Wigfield & Eccles, 2000), contributing positively to learning.

The advocacy for an accessible, encompassing platform allowing students to strategise their learning (e.g., to-do lists), participate actively in the instructional process (e.g., Mural digital whiteboard), conceptualise their learned knowledge (using tools like mind-maps), and retrospectively review and reflect on their learning journey (e.g., screen recorders) is underscored by the stages delineated in Zimmerman's self-regulation theory (Zimmerman, 2002).

Furthermore, the students' emphasis on time-management tools and self-recording options underscores the significance of metacognitive processes and self-monitoring in fostering SRL skills. The call for personal, customisable dashboards reflects an awareness of the need for user-friendly interfaces that accommodate individual learning styles and preferences (Bernacki et al., 2021; Roll & Winne, 2015).

Effective time management is pivotal in bolstering learning and memory retention. It facilitates managing cognitive resources, spacing study sessions, and reducing stress, culminating in enhanced memory consolidation. Theories such as the Spacing Effect, Cognitive Load Theory, and Stress and Coping Theory support the role of well-managed time in promoting recall (Cepeda et al., 2006), preventing cognitive overload, and minimising stress (Lazarus & Folkman, 1984) and memory functions (Sweller, 2011).

Volume 2. Issue 4. December 2024. Pages 1 to 21

Moreover, the students' call for human tutoring systems, reciprocal tutoring sessions, and educational advisory systems mirrors their desire for personalised support (Koedinger et al., 1997), fostering a sense of community and cultivating collaborative learning environments (Johnson & Johnson, 2009). This result aligns with the literature underscoring the social and emotional aspects (Schmid et al., 2022; Zimmerman & Schunk, 2001) and cognitive dimensions in bolstering SRL practices (Al-Kaabi, 2016).

In essence, the student's preferences for self-assessment tools, revision plans, peer matching, and recommendation systems within LA reflect a desire for tailored support, self-monitoring (Panadero et al., 2016), and cooperative learning (Dillenbourg, 1999), aligning with research on self-regulation that values metacognition, collaboration, and emotional factors in fostering effective learning (Zimmerman & Moylan, 2009).

Students' aspirations for receiving selective feedback are fortified by the Self-Determination Theory (Deci & Ryan, 2000), which suggests that autonomy in learning culminates in enhanced motivation and learning outcomes (Deci & Ryan, 2000). Moreover, the significance of feedback choice is highlighted by studies emphasising the differential effects on learning outcomes contingent on the type of feedback provided (Hattie & Timperley, 2007; Shute, 2008). Students' advocacy for human feedback and collaborative tools is corroborated by research in LA (Jivet et al., 2018), SRL (Laal & Ghodsi, 2012), and social constructivism (Palincsar, 1998), underscoring the interplay between technological and human contributions to enhancing education (Chen et al., 2018).

The current study's participants underscored the significance of incorporating "learner-controlled feedback" into the existing categories of LA feedback types, including descriptive, prescriptive, social, motivational, adaptive, evaluative, and corrective feedback (Hattie & Timperley, 2007; Siemens & Long, 2011). This novel category manifests a transformative shift in the locus of control, positioning learners as active agents in learning. Furthermore, learner-controlled feedback resonates with the self-determination theory, emphasising learner autonomy and self-direction (Deci & Ryan, 2000). In this context, learners assume ownership of their learning trajectories by choosing the criteria for feedback generation. Rubrics, wherein students relate their work to predefined success criteria, and peer feedback mechanisms, where students critique each other based on mutually agreed-upon criteria, exemplify learner-controlled feedback (Andrade, 2005). Empirical evidence supports learner-controlled feedback efficacy. For instance, Panadero and Alonso-Tapia (2014) demonstrated that students' self-defined success metrics led to enhanced performance over fixed criteria.

A crucial area warranting exploration in LA is the operationalisation of learner-controlled feedback, which entails creating an enabling environment where learners can customise their assessment criteria and incorporate or eliminate these from their personal LA dashboards. Drawing inspiration from specialised software like SPSS and MaxQDA, which empower researchers with customizability, similar capabilities can be extended to learners. As a result, this corresponds with the educational viewpoint of situating the student as an investigator, as endorsed by several learning theories. The practical execution of this dramatic change is a significant challenge for the LA community.

Overall, this study's results underscore the potential of LA to enhance SRL by integrating technology, facilitating human intervention and collaboration, and providing personalised learning experiences. These insights contribute to the growing body of literature on SRL theory (Zimmerman, 2002), highlighting the need for further research and practical implementation of these findings to optimise the adoption of LA in instructional contexts.

Conclusion

This research investigated the anticipations of highly self-regulated learners toward LA, a demographic typically underrepresented in scholarly discourse. The aim was to drive valuable insights to optimise design, addressing the gap between pedagogy and technology. The study incorporated the distinctive features of the SRL pedagogical lens and purposive sampling to further the discourse on LA design (Gašević et al., 2015). The findings revealed the significance of technology integration and dashboard customisation, human intervention and collaboration, personalised feedback, and learning recommendations for online SRL enhancement, corroborating existing literature on the subject (Sclater et al., 2016; Zimmerman, 2011).

In line with existing literature on learner autonomy and self-direction (Deci & Ryan, 2000) and Zimmerman's Theory of SRL (Zimmerman, 2000), the students' call for a transformative shift in the locus of control for receiving feedback from LA systems, incorporating learner-controlled feedback was another critical finding. However, the practical implementation of this paradigm shift presents a substantial challenge to the LA community (Joksimović et al., 2019).

The study's constraints warrant cautious consideration. The retrospective approach may cause recall bias, affecting the accuracy of participants' memories (Baxter & Jack, 2008). A limited sample size may affect the broader generalizability of the results. The sole reliance on qualitative methods could restrict the quantification and generalisation of the findings (Creswell & Poth, 2013). Despite its depth, purposive sampling may not reflect the wider population (Palinkas et al., 2015). These factors should be considered when interpreting the study's implications.

Prospective studies should encompass longitudinal, cross-cultural, and interventional methodologies (Tempelaar et al., 2015). Furthermore, technological and pedagogical innovations for including learner-controlled feedback in LA and meta-analytical evaluations warrant further investigation into the LA and SRL connection (Gašević et al., 2016).

Overall, this study enriches the intersectional knowledge of LA and SRL, providing intricate insights that can guide the development of technology-supported self-

Volume 2. Issue 4. December 2024. Pages 1 to 21

regulation tools. An essential implication of this research is that learning analytics should be designed to support students as active, research-oriented participants in their learning processes. Learning analytics must provide customisable feedback mechanisms to foster this approach that integrates qualitative and quantitative data, enabling students to select feedback types that best suit their self-regulatory needs and preferences (Chang et al., 2023; Fischer et al., 2020). Such personalised feedback options can enhance learners' engagement with feedback, promoting a more targeted and reflective approach to self-regulation (Fischer et al., 2020). Furthermore, establishing policies favours LA's strategic employment to bolster SRL. These perspectives are poised to form practical educational approaches, policy-making, and LA designs, thereby fostering online SRL by prioritising students' voices (Dawson et al., 2017; Ifenthaler & Schumacher, 2016).

Funding: This research did not receive a specific grant from public, commercial, or not-for-profit funding agencies.

Declaration of Competing Interest: The authors declare no competing interests.

References

Al-Kaabi, A. F. (2016). Effects of collaborative learning on the achievement of students with different learning styles at Qatar University. (Unpublished doctoral dissertation). Brunel University London.

Alfredo, R., Echeverria, V., Jin, Y., Yan, L., Swiecki, Z., Gašević, D., & Martinez-Maldonado, R. (2023). Human-centered learning analytics and AI in education: A systematic literature review. arXiv preprint arXiv:2312.12751.

Andrade, H. G. (2005). Teaching with rubrics: The good, the bad, and the ugly. *College Teaching*, *53*(1), 27–31.

Aniedu, A. N., Olibie, J. C., & Nwokoye, S. C. (2020). Speech recognition technology: An overview and practical implementation approach.

Arnold, K. E., & Sclater, N. (2017). Student perceptions of their privacy in learning analytics applications. In *Proceedings of the Seventh International Learning Analytics & Knowledge Conference*, 66–69.

Ary, D., Jacobs, L. C., Irvine, C. K. S., & Walker, D. (2018). *Introduction to research in education*. Cengage Learning.

Bahari, M., Arpaci, I., Azmi, N. F. M., & Shuib, L. (2023). Predicting the intention to use learning analytics for academic advising in higher education. *Sustainability*, *15*(21), 15190.

Baker, R., & Siemens, G. (2014). Learning analytics and educational data mining. *Cambridge Handbook of the Leaning Sciences*, 253–272.

Bartolomé, A., & Steffens, K. (2011). Technologies for self-regulated learning. In *Self-regulated learning in technology enhanced learning environments* (pp. 21–31). Brill Sense.

Baxter, P., & Jack, S. (2008). Qualitative case study methodology: Study design and implementation for novice researchers. *The Qualitative Report*, *13*(4), 544–559.

Bernacki, M. L., Greene, M. J., & Lobczowski, N. G. (2021). A systematic review of research on personalised learning: Personalised by whom, to what, how, and for what purposes? *Educational Psychology Review*, *33*(4), 1675–1715.

Birt, L., Scott, S., Cavers, D., Campbell, C., & Walter, F. (2016). Member checking: a tool to enhance trustworthiness or merely a nod to validation? *Qualitative Health Research*, *26*(13), 1802–1811.

Braun, V., & Clarke, V. (2021). Can I use TA? Should I use TA? Should I not use TA? Comparing reflexive thematic analysis and other pattern-based qualitative analytic approaches. *Counseling and Psychotherapy Research*, *21*(1), 37–47.

Brown, M. (2012). Learning analytics: Moving from concept to practice. *EDUCAUSE Learning Initiative*, *7*, 1–5.

Braun, V., & Clark, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77–101.

Campbell, J. L., Quincy, C., Osserman, J., & Pedersen, O. K. (2013). Coding in-depth semi-structured interviews: Problems of unitisation and intercoder reliability and agreement. *Sociological Methods & Research*, *42*(3), 294–320.

Cepeda, N. J., Pashler, H., Vul, E., Wixted, J. T., & Rohrer, D. (2006). Distributed practice in verbal recall tasks: A review and quantitative synthesis. *Psychological Bulletin*, *132*(3), 354.

Chang, D. H., Lin, M. P.-C., Hajian, S., & Wang, Q. Q. (2023). Educational design principles of using AI chatbot that supports self-regulated learning in education: Goal Setting, feedback, and personalisation. *Sustainability*, *15*(17), 12921.

Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *IEEE Access*, *8*, 75264–75278.

Crawford, J., Butler-Henderson, K., Rudolph, J., Malkawi, B., Glowatz, M., Burton, R., Magni, P. A., & Lam, S. (2020). COVID-19: 20 countries' higher education intra-period digital pedagogy responses. *Journal of Applied Learning & Teaching*, *3*(1), 1–20.

Creswell, J., & Poth, C. N. (2013). *Qualitative research and inquiry design: Choosing among five approaches. Lincoln,* University of Nebraska.

D'Mello, S., & Graesser, A. (2012). Dynamics of affective states during complex learning. *Learning and Instruction*, *22*(2), 145–157.

Dawson, S., Jovanovic, J., Gašević, D., & Pardo, A. (2017). From prediction to impact: Evaluation of a learning analytics retention program. In *Proceedings of the Seventh International Learning Analytics & Knowledge Conference*, 474–478.

Deci, E. L., & Ryan, R. M. (2000). The" what" and" why" of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry*, *11*(4), 227–268.

Deci, E. L., Ryan, R. M., & Williams, G. C. (1996). Need satisfaction and the self-regulation of learning. *Learning and Individual Differences*, *8*(3), 165–183.

Digel, S., Krause, T., & Biel, C. (2023). Enabling individualised and adaptive learning–The value of an AI-based recommender system for users of adult and continuing education platforms. *International Conference on Artificial Intelligence in Education*, 797–803.

Dillenbourg, P. (1999). *Collaborative learning: Cognitive and computational approaches.* Advances in Learning and Instruction Series. ERIC.

Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. *Review of Educational Research*, *74*(1), 59–109.

Fischer, C., Pardos, Z. A., Baker, R. S., Williams, J. J., Smyth, P., Yu, R., ... & Warschauer, M. (2020). Mining big data in education: Affordances and challenges. *Review of Research in Education, 44*(1), 130-160.

Gasevic, D., Dawson, S., & Pardo, A. (2016). How do we start? Sate and directions of learning analytics adoption.

Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends*, *59*, 64–71.

George, B., & Wooden, O. (2023). Managing the strategic transformation of higher education through artificial intelligence. *Administrative Sciences*, *13*(9), 196.

Gibbs, G. (1988). Learning by doing: A guide to teaching and learning methods. *Further Education Unit*.

Hamshin, G. G., Omar, A. Y., Said, O. S., & Saleh, S. S. (2023). Leveraging big data analytics to enhance E-learning services. *International Neurourology Journal*, *27*(4), 1529–1542.

Hattie, J., & Timperley, H. (2007). The power of feedback. *Review of Educational Research*, *77*(1), 81–112.

Hensley, L. C., Iaconelli, R., & Wolters, C. A. (2022). "This weird time we're in": How a sudden change to remote education impacted college students' self-regulated learning. *Journal of Research on Technology in Education*, *54*(sup1), S203–S218.

Ifenthaler, D., & Schumacher, C. (2016). Student perceptions of privacy principles for learning analytics. *Educational Technology Research and Development*, *64*, 923–938.

Ifenthaler, D., & Widanapathirana, C. (2014). Development and validation of a learning analytics framework: Two case studies using support vector machines. *Technology, Knowledge and Learning*, *19*(1), 221–240.

Jafari, E. (2024). The challenges and strategies in Iranian higher education: the post-COVID age. *Educational Research for Policy and Practice*, *23*(1), 135–156.

Jivet, I., Scheffel, M., Specht, M., & Drachsler, H. (2018). License to evaluate: Preparing learning analytics dashboards for educational practice. In *Proceedings of the 8th International Conference on Learning Analytics and Knowledge*, 31–40.

Johnson, D. W., & Johnson, R. T. (2009). An educational psychology success story: Social interdependence theory and cooperative learning. *Educational Researcher*, *38*(5), 365–379.

Joksimović, S., Kovanović, V., & Dawson, S. (2019). The journey of learning analytics. *HERDSA Review of Higher Education*, *6*, 27–63.

Jones, K. M. L., Asher, A., Goben, A., Perry, M. R., Salo, D., Briney, K. A., & Robertshaw, M. B. (2020). "We're being tracked at all times": Student perspectives of their privacy in relation to learning analytics in higher education. *Journal of the Association for Information Science and Technology*, *71*(9), 1044–1059.

Knight, S., Buckingham Shum, S., & Littleton, K. (2013). Collaborative sensemaking in learning analytics.

Koedinger, K. R., Anderson, J. R., Hadley, W. H., & Mark, M. A. (1997). Intelligent tutoring goes to school in the big city. *International Journal of Artificial Intelligence in Education*, *8*(1), 30–43.

Kurni, M., Mohammed, M. S., & Srinivasa, K. G. (2023). Predictive Analytics in Education. In *A Beginner's Guide to Introduce Artificial Intelligence in Teaching and Learning* (pp. 55–81). Springer.

Laal, M., & Ghodsi, S. M. (2012). Benefits of collaborative learning. *Procedia-Social and Behavioral Sciences*, *31*, 486–490.

Lazarus, R. S., & Folkman, S. (1984). *Stress, appraisal, and coping*. Springer Publishing Company.

Majid, I., & Lakshmi, Y. V. (2020). Artificial Intelligence in Education. *NATIONAL*, *18*(2), 106.

McLoughlin, C., & Lee, M. J. W. (2010). Personalised and self-regulated learning in the Web 2.0 era: International exemplars of innovative pedagogy using social software. *Australasian Journal of Educational Technology*, *26*(1).

Nouri, J., Ebner, M., Ifenthaler, D., Sqr, M., Malmberg, J., Khalil, M., Bruun, J., Viberg, O., González, M. Á. C., & Papamitsiou, Z. (2019). Efforts in Europe for data-driven improvement of education–A review of learning analytics research in six countries.

Nunnally, J. C. (1978). *Psychometric Theory (2nd ed.).* McGraw-Hill.

Palincsar, A. S. (1998). Social constructivist perspectives on teaching and learning. *Annual Review of Psychology*, *49*(1), 345–375.

Palinkas, L. A., Horwitz, S. M., Green, C. A., Wisdom, J. P., Duan, N., & Hoagwood, K. (2015). Purposeful sampling for qualitative data collection and analysis in mixed method implementation research. *Administration and Policy in Mental Health and Mental Health Services Research*, *42*, 533–544.

Panadero, E. (2017). A review of self-regulated learning: Six models and four directions for research. *Frontiers in Psychology*, *8*, 422.

Panadero, E., & Alonso-Tapia, J. (2014). How do students self-regulate? Review of Zimmerman's cyclical model of self-regulated learning. *Anales de Psicologia*, *30*(2), 450–462.

Panadero, E., Brown, G. T. L., & Strijbos, J.-W. (2016). The future of student self-assessment: A review of known unknowns and potential directions. *Educational Psychology Review*, *28*, 803–830.

Park, Y., & Jo, I.-H. (2015). Development of the learning analytics dashboard to support students' learning performance. *Journal of Universal Computer Science*, *21*(1), 110.

Paudel, P. (2021). Online education: Benefits, challenges, and strategies during and after COVID-19 in higher education. *International Journal on Studies in Education (IJonSE)*, *3*(2).

Pedrotti, M., & Nistor, N. (2019). How students fail to self-regulate their online learning experience. In *Proceedings of European Conference on Technology Enhanced Learning*, (pp. 377–385).

Pekrun, R. (2006). The control-value Theory of achievement emotions: Assumptions, corollaries, and implications for educational research and practice. *Educational Psychology Review*, *18*, 315–341.

Pilling-Cormick, J., & Garrison, D. R. (2007). Self-directed and self-regulated learning: Conceptual links. *Canadian Journal of University Continuing Education*, *33*(2).

Pintrich, P. R., Marx, R. W., & Boyle, R. A. (1993). Beyond cold conceptual change: The role of motivational beliefs and classroom contextual factors in the process of conceptual change. *Review of Educational Research*, *63*(2), 167–199.

Rajeh, M. T., Abduljabbar, F. H., Alqahtani, S. M., Waly, F. J., Alnaami, I., Aljurayyan, A., & Alzaman, N. (2021). Students' satisfaction and continued intention toward e-learning: A theory-based study. *Medical Education Online*, *26*(1), 1961348.

Ritchie, J., Lewis, J., Nicholls, C. M., & Ormston, R. (2013). *Qualitative research practice: A guide for social science students and researchers*. Sage.

Roberts, L. D., Howell, J. A., Seaman, K., & Gibson, D. C. (2016). Student attitudes toward learning analytics in higher education: "The Fitbit version of the learning world." *Frontiers in Psychology*, *7*, 1959.

Roll, I., & Winne, P. H. (2015). Understanding, evaluating, and supporting self-regulated learning using learning analytics. *Journal of Learning Analytics*, *2*(1), 7–12.

Romero, C., & Ventura, S. (2010). Educational data mining: a review of the state of the art. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, *40*(6), 601–618.

Sajja, R., Sermet, Y., Cwiertny, D., & Demir, I. (2023). Integrating AI and Learning Analytics for Data-Driven Pedagogical Decisions and Personalised Interventions in Education. *ArXiv Preprint ArXiv:2312.09548*.

Schmid, R., Pauli, C., Stebler, R., Reusser, K., & Petko, D. (2022). Implementation of technology-supported personalised learning—its impact on instructional quality. *The Journal of Educational Research*, *115*(3), 187–198.

Schumacher, C., & Ifenthaler, D. (2018). Features students really expect from learning analytics. *Computers in Human Behavior*, *78*, 397–407.

Sclater, N., Peasgood, A., & Mullan, J. (2016). Learning analytics in higher education. *London: Jisc. Accessed February*, *8*(2017), 176.

Sedrakyan, G., Malmberg, J., Verbert, K., Järvelä, S., & Kirschner, P. A. (2020). Linking learning behavior analytics and learning science concepts: Designing a learning analytics dashboard for feedback to support learning regulation. *Computers in Human Behavior*, *107*, 105512.

Selwyn, N. (2019). *Should robots replace teachers?: AI and the future of education*. John Wiley & Sons.

Shemshack, A., Kinshuk, & Spector, J. M. (2021). A comprehensive analysis of personalised learning components. *Journal of Computers in Education*, *8*(4), 485–503.

Shute, V. J. (2008). Focus on formative feedback. *Review of Educational Research*, *78*(1), 153–189.

Siemens, G., & Baker, R. S. J. d. (2012). Learning analytics and educational data mining: towards communication and collaboration. In *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge*, (pp. 252–254).

Siemens, G., & Long, P. (2011). Penetrating the fog: Analytics in learning and education. *EDUCAUSE Review*, *46*(5), 30.

Silverman, D. (2013). *Doing qualitative research: A practical handbook*. Sage.

Simonson, M., Zvacek, S. M., & Smaldino, S. (2019). *Teaching and learning at a distance: Foundations of distance education* (7th ed.).

Sweller, J. (2011). Cognitive load theory. In *Psychology of learning and motivation* (Vol. 55, pp. 37–76). Elsevier.

Syndicate, U. (2001). Quick placement test. Oxford: Oxford University Press.

Tempelaar, D. T., Rienties, B., & Giesbers, B. (2015). In search for the most informative data for feedback generation: Learning analytics in a data-rich context. *Computers in Human Behavior*, *47*, 157–167.

Tapalova, O., & Zhiyenbayeva, N. (2022). Artificial Intelligence in Education: AIEd for Personalised Learning Pathways. *Electronic Journal of E-Learning*, *20*(5), 639–653.

Tracy, S. J. (2024). *Qualitative research methods: Collecting evidence, crafting analysis, communicating impact. John Wiley & Sons.*

Tsai, Y.-S., Whitelock-Wainwright, A., & Gašević, D. (2020). The privacy paradox and its implications for learning analytics. In *Proceedings of the Tenth International Conference on Learning Analytics & Knowledge*, (pp. 230–239).

Volume 2. Issue 4. December 2024. Pages 1 to 21

Vishwakarma, A., & Tyagi, N. (2022). Strategies for Promoting Self-Regulation in Online Learning Environment: An Analytical Review. *Journal of Positive School Psychology*, *6*(2), 4258–4271.

Whitelock-Wainwright, A., Gašević, D., Tejeiro, R., Tsai, Y., & Bennett, K. (2019). The student expectations of learning analytics questionnaire. *Journal of Computer Assisted Learning*, *35*(5), 633–666.

Wigfield, A., & Eccles, J. S. (2000). Expectancy–value theory of achievement motivation. *Contemporary Educational Psychology*, *25*(1), 68–81.

Wise, A. F., Knight, S., & Shum, S. B. (2021). Collaborative learning analytics. In *International Handbook of Computer-Supported Collaborative Learning*, (pp. 425–443).

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education–where are the educators? *International Journal of Educational Technology in Higher Education*, *16*(1), 1–27.

Zheng, L., Fan, Y., Gao, L., & Huang, Z. (2023). The impact of learning analytics interventions on learning achievements: A meta-analysis of research from 2012 to 2021. *Interactive Learning Environments*, 1–16.

Zimmerman, B. J. (2000). Attaining self-regulation: A social cognitive perspective. In *Handbook of self-regulation* (pp. 13–39). Elsevier.

Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. *Theory into Practice*, *41*(2), 64–70.

Zimmerman, B. J. (2011). Motivational sources and outcomes of self-regulated learning and performance: In *Handbook of self-regulation of learning and performance* (pp. 63–78). Routledge.

Zimmerman, B. J., & Moylan, A. R. (2009). Self-regulation: Where metacognition and motivation intersect. In *Handbook of metacognition in education* (pp. 299–315). Routledge.

Zimmerman, B. J., & Schunk, D. H. (2001). *Self-regulated learning and academic achievement: Theoretical perspectives*. Routledge.