Journal of Information Systems Engineering and Management
2025, 10(11s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Artificial Intelligence and Human-Centered in Linguistic Analysis: Self-Regulated Learning and Development

Dr. N. Vijayalakshmi[1], Dr. Saravanan R[2], R.Jayalakshmi[3], R. Rekha[4], Dr. K. Indumathy[5]

[1]*Assistant Professor (Sr. G), Programme Coordinator Data Science, Department of Computer Science and Applications, SRMIST, Ramapuram Campus, Chennai. vijayaln@srmist.edu.in*

[2]*Professor, Department of Information Technology, Sri Manakula Vinayagar Engineering College, Puducherry. rsaravanan26@gmail.com*

[3]*Assistant Professor, Department of Computer Science and Engineering, Rajiv Gandhi College of Engineering and Technology, Puducherry. jaya.toysmile@gmail.com*

[4]*Assistant Professor, Department of Computer Science and Business Systems, Panimalar Engineering College, Chennai. rekhuradha@gmail.com*

[5]*Associate Professor, Department of Computer Science and Applications, Christ College Arts and Science, Puducherry. indumathyonlinecoach@gmail.com*

ARTICLE INFO

Received: 05 Nov 2024

Revised: 20 Dec 2024

Accepted: 12 Jan 2025

ABSTRACT

Recently, learning approaches have utilized Artificial Intelligence (AI) and the Internet of Things (IoT) to create an efficient learning environment. The application of IoT and AI to improve learning systems is thoroughly examined in this paper. Additionally discussed are various IoT and AI-based approaches and strategies related to e-learning, M-learning, methods employed, and particular applications. A new era of linguistic and literary analysis is ushered in by the convergence of technology and the humanities. The creative ways that artificial intelligence provides for comprehending and interpreting texts make it relevant. As it enables the discovery of meaning, style, and other aspects of language usage in texts, linguistic analysis of texts is a crucial component of philological investigation. In this human-centric paradigm, it also becomes imperative to investigate how AI aligns with human values. In particular, giving in-service teachers examples of how to apply the suggested framework improved their understanding of generative AI concepts and how to incorporate them into their instruction. To handle learning techniques more effectively, the results of this evaluation will guide the creation of strategies that combine IoT and AI.

Keywords: machine learning (ML), human-centricl, Linguistic Analysis, human values, Self-Regulated Learning.

INTRODUCTION

A period of significant change in many fields, including education, has been brought about by the development of AI. The ability of generative AI to produce text, audio, images, videos, and programming code is one of its defining characteristics. Compared with its quick adoption in industries like software engineering, healthcare, and business operations, generative AI has yet to be fully incorporated into educational settings, despite its enormous promise. The reason for this lag is that teachers' contributions to the implementation and coordination of AI tools have not received enough attention [1]. A strong framework that facilitates teaching and learning is necessary to incorporate creative AI tools into educational processes. Foundational criteria for integrating generative AI in education have been established by current structures, such as those supported by the Australian government's efforts and the United Nations Educational, Scientific, and Cultural Organization (UNESCO). Nevertheless, there is a clear lack of application of these frameworks to the real-world application of generative AI in K–12 classrooms. In particular, to empower educators and help students fully utilize generative AI techniques; specific classroom-level coaching is required.

According to the idea of self-regulated learning (SRL), a student who practices SRL is successful because they can command and regulate their actions by a learning objective, therefore controlling the learning environment. Interaction with the learning process, such as actively interacting with the content, modifying one's behaviors to meet learning objectives, and taking accountability for the learning results, are characteristics of SRL. Teaching metacognitive techniques, encouraging goal-setting, cultivating a growth attitude, and offering constructive criticism are all part of implementing SRL in the classroom [2]. Even though diverse theories and models provide distinct viewpoints, they all concur that SRL includes the overarching goals of goal-setting, plan execution, and process assessment.

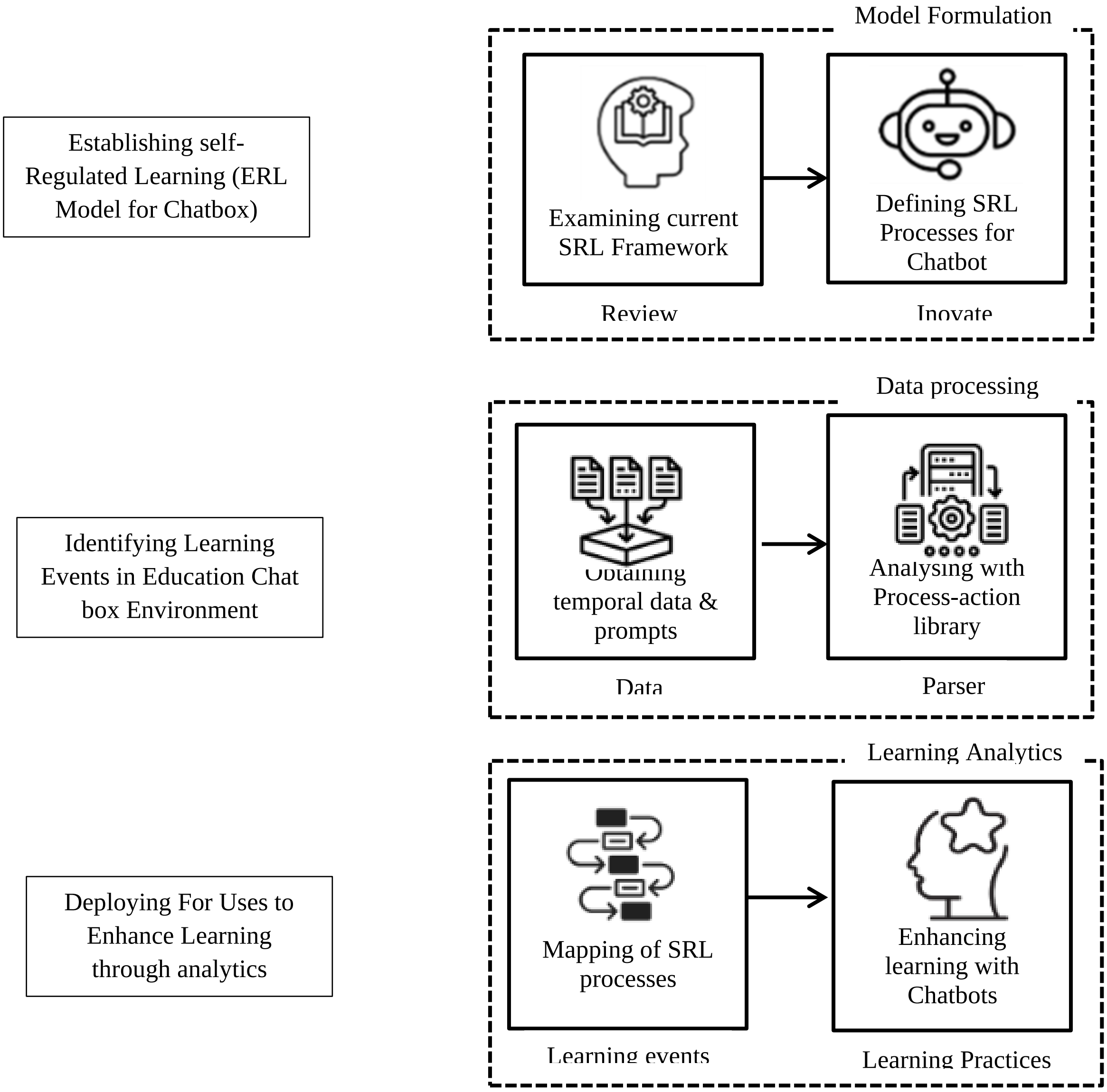

Figure 1.1: Building a framework for the SRL model using a learning analytics process map

Studies on kids who struggle academically or have learning disabilities typically show poorer metacognition and self-regulated learning. Students with learning disabilities may benefit academically from some therapies, such as the development of self-regulated strategies [3]. According to certain research, girls typically perform better than boys in self-regulated learning; this pattern holds true for all educational levels and nations. Studies have shown that metacognitive self-regulated learning is essential for academic success. Effective metacognitive learners are able to set goals, monitor their progress, and adapt to changing learning environments.

However, research on using AI technology to support metacognitive self-regulated learning is still in its infancy. The challenge for educational institutions in our quickly changing environment is to teach all the skills needed for the future. Thus, teaching pupils "how to learn" should take precedence above merely imparting facts. Through education, metacognitive and self-learning abilities can be fostered. The updated Bloom's taxonomy has included metacognitive skills at different educational levels in recognition of their critical function.

We look at the current SRL frameworks in Section 2 to address these research questions. We will compile our research from the current frameworks to create a new framework that can be used to analyze SRL in the given prompts. We then examine two students' interactions with a chatbot as a proof-of-concept, categorizing the prompts using the framework in Section 3. In Section 4, the different learning process phases are arranged and published after being analyzed for learning analytics. Figure 1.1 shows the scope for creating an SRL model framework for a GenAI chatbot.

RELATED WORKS

The student actively and productively participates in the learning process rather than merely passively absorbing knowledge. This engagement comprises the capacity to keep an eye on, manage, and control elements of motivation, behavior, cognition, and the environment. The learner compares their progress using criteria, making adjustments as needed [4]. Results like performance or achievement are not exclusively determined by environmental or personal factors. Rather, the relationship between these elements and performance results is mediated by the learner's self-regulation of motivation, behavior, and cognition. Building on this, we define self-regulated learning as "an active, constructive process whereby learners set goals for their learning and then try to monitor, regulate, and control their cognition, motivation, and actions guided and constrained by their goals and the contextual features in the environment."

Both the AI-assisted and non-AI-assisted groups in the present research participate in interactive language learning exercises, which is closely in line with Vygotsky's social constructivist theory. In the control group, students engage with their peers and support one another's language learning journeys [5], thereby increasing each other's ZPD. In contrast, the experimental group uses an AI-assisted language learning tool that acts as a cooperative partner for language acquisition. The foundation of our research is the way in which learners use AI technology to control their language acquisition and move closer to their ZPD through these interactions.

The first method places a strong emphasis on visually represented representations of data-driven feedback, frequently showcasing the performance and learning activities of a class as a whole or of individual individuals. Purdue Course Signals, an Early Warning System that uses traffic light signals to identify a student's likelihood of passing a course and alert teachers to provide support, is an early example [6]. The LASSI dashboard is another example of a dashboard that focuses on the development of self-regulated learning skills. It uses unit-chart visualization to show comparison data between individuals and the cohort regarding student time management, motivation, concentration, test strategies, and failure anxiety.

The IPT approach [7] explains how context impacts SRL while also making certain unique assumptions. This idea states that students' judgments of the learning task are influenced by contextual information to some extent. According to this theory, SRL is cyclical, meaning that data processed in one stage can be used as input for data processing in later stages.

For instance, teachers that encourage metacognitive monitoring might help pupils with this crucial SRL component. Theoretical presumptions on the significance of context and established empirical links between SRL and learning results have given rise to suggestions that classroom instruction go beyond merely imparting factual knowledge. Competencies with the learning process, like students' capacity to control their own learning, have been suggested as a primary, clear goal of education.

The processes that can help or hinder academic success are the focus of our study on self-regulated learning. We are interested in the ways that successful and failed students approach learning differently [8], are more driven to learn new things, and are aware of suitable techniques. We think that students develop several "theories of training" that shape what they do in the classroom and establish courses that impact a lifetime of learning actions and competencies. Social relationships in the classroom offer the data that supports these views. Implicit notions and beliefs about one's own skills, expectations for future achievement, the types of academic problems, the availability and utility of cognitive methods, and the social dispositions of others in the classroom are all formed by schoolchildren. Children's self-regulated learning is mediated by these ideas, even if they are implicit and incomplete. As they get older, they are able to consider these beliefs and express them more clearly.

Due to technological advancements, SRL research has expanded from in-person settings to other settings. Some empirical research on self-regulation in technology-enhanced learning environments (TELEs) is one example. They divided the TELEs into three categories: unenhanced, which do not improve SRL [9]; didactic, which educate students how to self-regulate; and enabling, which have resources to facilitate SRL but do not encourage its use. In their findings, these writers also stress the connection between student behavior and the learning environment, as well as the significance of adaptable settings to accommodate each learner's unique needs. In terms of online settings, the relationship that exists between SRL tactics and learning achievements in in-person settings also holds true in online settings. However, it seems that the benefits of conventionally helpful SRL techniques, including elaboration, are less pronounced in virtual settings.

To say that there have been no studies examine the expectations of LA's stakeholders would be incorrect, as the literature study indicates. But as far as we are aware, not many research have examined LA through the SRL pedagogical lens. Additionally, as far as we are aware, no research has looked into how highly self-regulated students view LA's potential to help them develop their online self-regulation abilities. In order to close this gap, the current study focuses on the expectations of highly self-regulated learners of LA as a crucial source of knowledge on increasing SRL [10]. Furthermore, by utilizing a retrospective methodology, an SRL pedagogical lens, and the unique characteristics of purposive sampling of highly self-regulated learners, the current study goes beyond the existing literature. Thus, from the viewpoint of a neglected yet extremely informative set of learners, the current study also aims to address the crucial topic of how LA may improve online SRL.

METHODS AND MATERIALS

Human-Centered Analytics with AI for Learning

The insights that artificial intelligence and learning analytics (LA) offer into teaching and learning methodologies have made their integration into education crucial. Monitoring learning progress, reducing administrative work, and providing timely, individualized feedback are all made possible by implementing LA and AI technologies. For instance, adaptive platforms enable real-time feedback, LA dashboards enable educators to track students' progress, intelligent tutoring tools can tailor lessons to each student's unique learning style and pace, and AI-based virtual assistants can provide prompt assistance in a more interactive setting by answering questions and supplying extra resources.

However, only a small percentage of people are now using these technologies. The absence of transparent tools, adoption costs, and institutional policies are some of the elements that may be causing this resistance [11]. Many authors also criticize the lack of pedagogical principles, the lack of environmental relevance, and the disregard for human needs. Previous study emphasized the significance of human-centered design (HCD) for building LA and systems in order to take human requirements, values, and perceptions into account.

When developing technical solutions, HCD views stakeholders as partners. For example, the goals and structure of their courses are best understood by the professors. Their knowledge may be quite helpful when creating LA or AI tools to make sure that suggested solutions enhance learning rather than impede it. HCD can improve human potential, reveal obstacles, and promote use of technology.

Customizing Educational Activities to Promote Personalized Learning

To find out how the unique features of lifelong learning should be incorporated into modified or new learner models, more research should be done.

Furthermore, lifelong learner models that go beyond the conventional parameters of knowledge and competency assessment should be developed in future research. These models ought to offer a comprehensive perspective on students, taking into account socioeconomic considerations, job requirements, motivation, engagement, learning habits and techniques, and professional development [12]. This can be accomplished by combining various learner models using ensemble techniques, or by employing multi-objective, multi-task, or multi-modal instructor models.

Providing Control and Explain ability for AI-Assisted Educational Systems

First, rather than just improving learners' comprehension of AI systems and their results [13], it's critical to create practical explanations that support them in making wise judgments. Second, prior research has demonstrated encouraging trends in the direction of personalizing explanations, such as by tailoring the explanation type to individual characteristics. Third, it is important to appropriately assess the effectiveness of explanations, taking into account factors like comprehending, effective trust-building, and the growth of cognition.

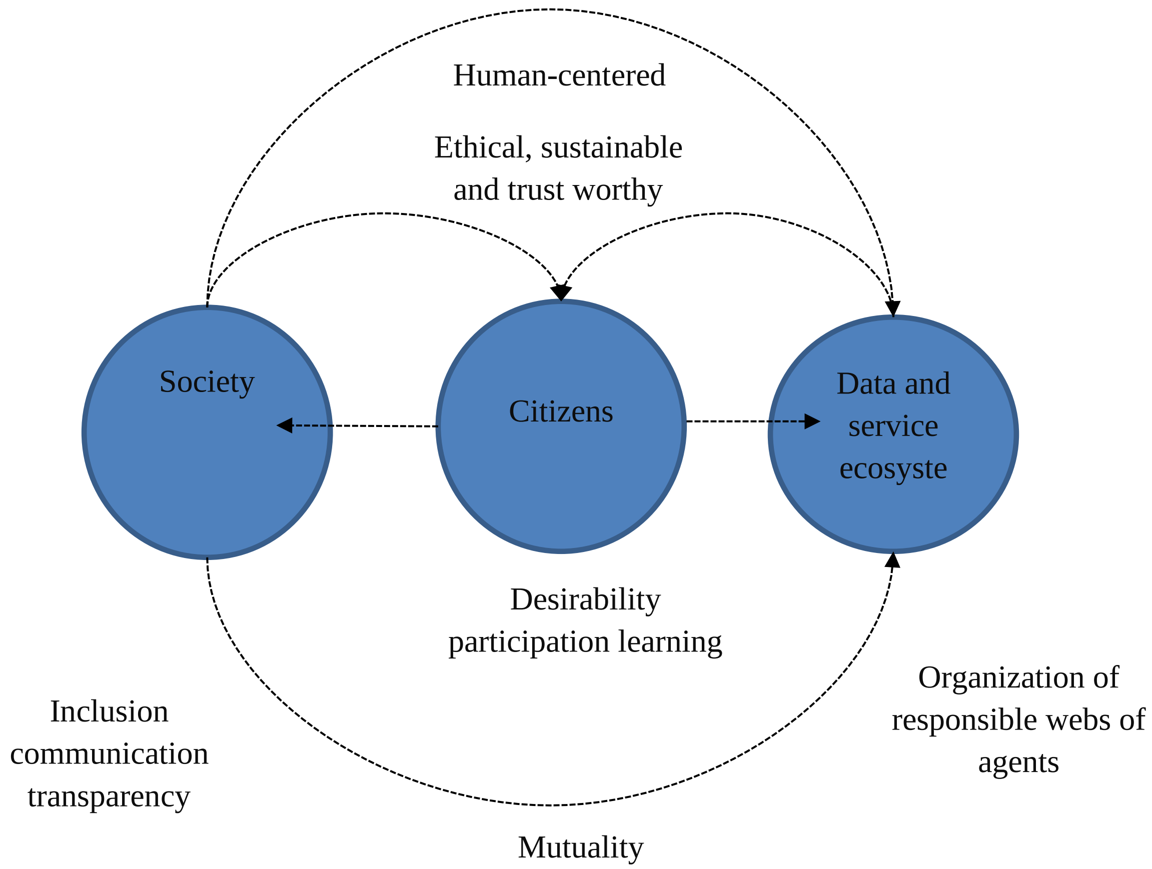

Figure 3.1: A comprehensive strategy for the creation and application of human-centered AI

Figure 3.1 summarizes the points made in this research and shows how we believe HCAI may be viewed as a governance viewpoint that encourages the development of emancipatory technologies [14]. The image illustrates how the systemic method to human-centered AI development promotes inclusive and sustainable societal growth, which is based on openness and dialogue in the making of decisions. The concept of mutuality between public authorities and various agents in data and service ecosystems—which can be thought of as accountable webs of agents—should be the foundation for AI development and implementation.

Government initiatives pertaining to AI should encourage and support public discussion about the benefits of AI, including citizen engagement, and advance knowledge and comprehension of AI and AI ethics.

Because they facilitate widespread participation and involvement in decision-making processes, collaborative and civic technology solutions can aid in operationalizing the holistic and inclusive approach.

The nature, deadlines, and imaginations of both participatory and deliberative decision-making, as well as the mutual appropriateness of technology, could be altered by stakeholder and citizen engagement and participation innovations. Concrete tools and techniques for extensive discussion, widespread participation, and ways to compile and process choices in ways not previously achievable are offered by civil engagement literature and case studies. While these engagement tools have, in spite of their potential, typically failed to influence fundamental democratic processes in the past, new frameworks for AI governance may take into account the innovations [15]' interest and constraints in enhancing the actionability of moral principles and supporting human-centered, socially sustainable artificial intelligence governance.

IMPLEMENTATION AND EXPERIMENTAL RESULTS

L2 learners' writing self-efficacy characteristics

The exploratory LPA was used to determine the writing self-efficacy profiles of L2 students. We looked at three solutions: the two-profile, three-profile, and four-profile. Higher chaos, lower AIC, BIC, and aBIC, as well as the significant p values for LMR and BLRT, were all taken into consideration while choosing the latent profile that best fits the data. In terms of the indicator variables, the selected profiles could also be examined to determine whether they qualitatively differ from one another. Table 1 displays the LPA findings for the three solutions.

Table 1: The outcomes of the LPA

C	K	AIC	BIC	aBIC	Entrophy	LMR	BLRT
2	58	29463.678	29657.245	29501.761	.792	.0005	.0000
3	75	28786.452	29048.487	28838.872	.818	.0061	.0000
4	92	28614.805	28944.308	28679.953	.787	.2657	.0000

Figure 4.1 shows the individuals assigned to Profile 1 had low scores on all indicator items related to self-efficacy in language, self-regulation, academic performance, and genre-based performance; participants entrusted to Profile 2 had average scores on all indicator items; and subjects assigned to Profile 3 had high scores on all items. In comparison to linguistic self-efficacy, self-regulatory self-efficacy, and genre-based perform self-efficacy, those involved in the three profiles generally scored lower on classroom performance self-efficacy [16]. "Low on All Self-Efficacy," "Average on All Self-Efficacy," and "High on All Self-Efficacy" are the labels we assigned to Profiles 1 through 3, appropriately.

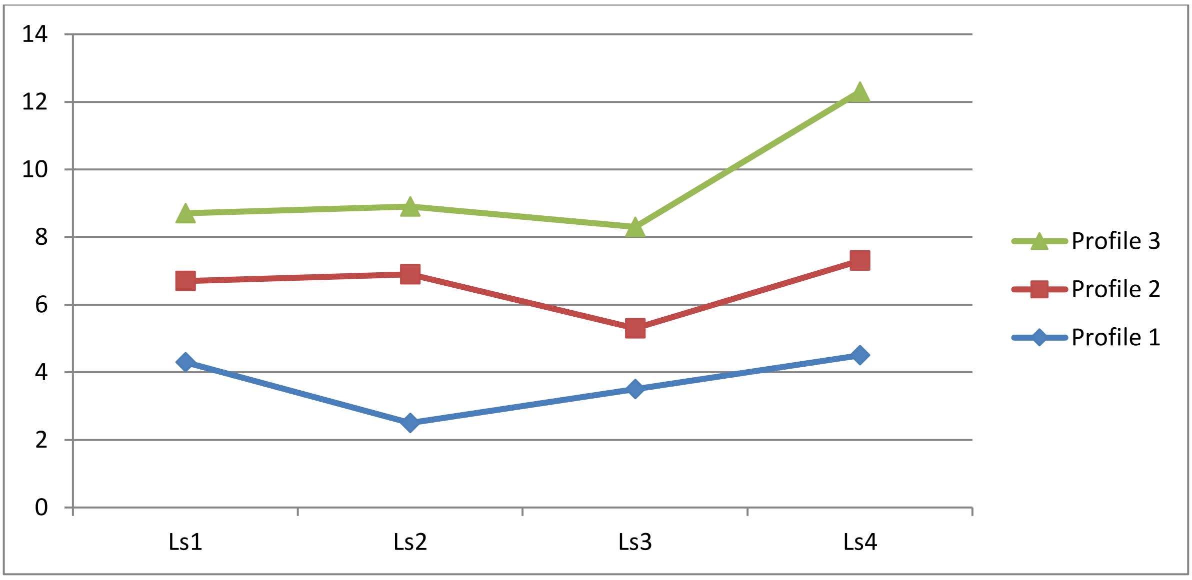

Figure 4.1: Three self-efficacy writing profiles

Language self-efficacy is represented by LS, self-regulatory self-efficacy by SRS, classroom performance self-efficacy by CPS, and genre-based performance self-efficacy by GPS.

The L2 students in the study's sample showed three distinct writing self-efficacy profiles: "lower on All Self-Efficacy," "normal" on All Self-Efficacy," or "Excellent on All Self-Efficacy." This outcome is similar to the three levels of self-efficacy for learning English that were identified among EFL learners who speak Korean: low, middle, and high. The present study differs from previous conceptualizations of self-efficacy in that it used the unitary notion of self-efficacy and based LPAs on the average score of all the questions used to measure self-efficacy as a multifaceted construct, and as Figure 4.1 shows [17], the LPAs were founded on every item.

Variations by profile in how writing self-efficacy predicts SRL composing methods

The predictive impacts of L2 pupil self-efficacy on their use of SRL writing strategies were investigated using path analyses, which also reveal that the frameworks are completely full based on the equation's fit indices. Table 2 shows the outcomes of the path analysis.

Table 2: Variations in writing self-efficacy's ability to predict SRL writing methods

	Factors	Overall		Profile 1	Profile 2	Profile 3
		β	ρ	β	β	β
TR	LS	.348	.001	.088	.185	.214
	SRS	.345	.001	.118	.286	.29
	CPS	-.188	.128	.033	-.222	.017
	GPS	.24	.053	.188	.183	-.228
PL	LS	.154	.482	.005	.195	.013
	SRS	.364	.001	.35	.297	.197
	CPS	.32	.003	-.056	.275	.323
	GPS	-.155	.541	-.013	-.127	-.189
FH	LS	.236	.135	.068	.246	.142
	SRS	.476	.001	.528	.299	.439
	CPS	-.308	.005	-.413	-.198	-.308
	GPS	-.142	.656	-.003	-.144	-.146
IE	LS	.15	.565	.052	-.02	.214
	SRS	.472	.001	.297	.444	.354
	CPS	.182	.287	-.007	.158	.182
	GPS	-.125	.824	-.016	1.33	-.224
MST	LS	.203	.153	.017	.209	.283
	SRS	.573	.001	.563	.518	.342
	CPS	-.139	.627	-.187	-.117	.212
	GPS	.15	.621	-.146	.188	.136

The predictive impacts of SRL writing techniques and writing self-efficacy on writing successes were examined using path analysis to identify variations between writing self-efficacy characteristics. The model fit indices of the proposed models for path analyses are detailed in Table 3, which demonstrates that these frameworks are fully saturated. Table 4 shows the outcomes of the path analysis.

Table 3: Indicators of model fit for path analysis frameworks

	X^2	df	CFI	TLI	RMSEA	SRMR	AIC	BIC
Profiles	1	1	2	2	1	1	3652.546	3783.063
Overall	1	1	2	2	1	1	3624.387	3668.043

Table 4: Disparities in the ability of SRL writing techniques along with self-efficacy to predict writing accomplishments

Factors	Overall		Profile 1		Profile 2		Profile 3	
	β	ρ	β	ρ	β	ρ	β	ρ
LS	.134	.042	.013	.944	.118	.20	.166	.159
SRS	-.034	.613	.017	.918	.024	.770	-.079	.508
CPS	-.005	.963	.12	.559	.001	.989	.070	.520
GPS	.178	.014	.127	.372	.185	.047	-.072	.614
TR	-.017	.79	-.039	.847	-.035	.642	-.05	.742
PL	-.018	.762	.102	.533	.036	.683	-.177	.170
FH	.035	.60	.248	.157	.026	.78	-.035	.863
IE	-.003	.976	.107	.544	-.045	.573	-.033	.846
MST	-.130	.07	-.47	.012	-.156	.195	.060	.769

Variations by profile in the predicted impact of composing self-efficacy on SRL writing techniques

According to path analysis results, the entire sample's self-efficacy in linguistics might predict how they would use text revisions and input handling; how they would use peer knowledge and feedback handling in the classroom; and how they would utilize all SRL writing strategies if they had self-regulatory self-efficacy. These results let us better understand the nuances of the predicted effects of compose self-efficacy on SRL writing for L2 students who took part in creating self-efficacy profiles. None of the profiles identified demonstrated the statistical impact of linguistics self-efficacy on handling criticism; only the Maximum on All Self-efficacy Profile shown this predictive influence on text revision. In a similar vein, only the Average on All Self-efficacy Profile demonstrated the predictive influence of educator self-efficacy on peer learning; in contrast, the findings for the predictive role of classroom performance self-efficacy on feedback management showed the opposite conclusion.

Additionally, while the Low on All Self-efficacy Profile did not replicate the predictive impact of self-regulatory self-efficacy on text revision and interest augmentation, the Average on All Self-efficacy Profiling and the High on All Self-efficacy Profile did. The prospective effects of self-regulatory self-efficacy on peer learning, however, were reproduced by the Normal on All Self-efficacy Profile and the Low on All Self-efficacy Profile rather than the High on All Self-efficacy Profile [18]. However, the current study also found that the established profiles consistently showed the predictive impact of self-regulatory self-efficacy on handling constructive criticism and positive self-talk.

The profiles' and the whole sample's disparate prediction impacts of writing self-efficacy on SRL writing methods raise the possibility that crucial subgroup distinctions between these effects may be hidden by the conventional variable-centered methodology. The profiles' and the whole sample's disparate prediction impacts of writing self-efficacy on SRL authoring methods raise the possibility that crucial subgroup distinctions between these effects may be hidden by the conventional variable-centered methodology.

Variations in the predicted impact of SRL writing techniques and writing self-efficacy on L2 writing success by profile

Path analyses showed that all participants' writing achievement was significantly predicted by their level of language and genre performing self-efficacy, which may further support the significance of these traits. However, the path analyses found that the predictive influence of SRL writing methods and writing self-efficacy varied among profiles of writing self-efficacy. In particular, only their genre-based performing self-efficacy had a meaningful effect on their writing achievement for the Good on All Self-efficacy profile, while only their motivating self-talk could adversely predict their writing achievement for the Low on All Self-efficacy profile. On the other hand, neither SRL writing methods nor aspects of writing self-efficacy were significant markers of writing accomplishment for those with the High on All Self-efficacy character.

By revealing additional specifics about how these effects differ among various subgroups, our understanding of these effects may be improved by examining the profile differences in the predictive effects of written self-efficacy and SRL writing techniques on writing success..

Furthermore, the profile disparities in these effects may indicate that L2 students' writing performance will not increase in tandem with their growth and improvement in writing self-efficacy. Furthermore, using L2 students' writing self-efficacy to forecast their writing success should be done with caution.

CONCLUSION

Even while artificial intelligence offers encouraging prospects for promoting lifelong learning, there are still many obstacles to overcome. The adaptability of personalized lifelong learning, the explainability and controllability of AI-supported learning systems, and human-centered learning analytics and AI with a focus on keeping stakeholders informed were the three main subjects covered in this study. It is far from easy to advance the AIEd field in these areas, particularly when both algorithmic and human-centered skills are needed. Therefore, we advocate for ongoing interdisciplinary collaboration at all phases of the design, development, and research process for AI-supported educational technologies to benefit all stakeholders in the context of lifelong learning.

The results may have some ramifications for L2 writing studies and teaching methods. In terms of methodology, we may be able to uncover group-level differences in L2 instructional self-efficacy by using the LPAs to identify various profiles. This would give us a starting point for examining the variations in the predictive influence of written self-efficacy on SRL writing techniques and their consequences for the success of L2 writing. By identifying writing self-efficacy profiles, educators can gain insight into the nuances of L2 students' writing self-efficacy. Additionally, the correlations between SRL writing techniques and the impact of self-efficacy on writing success, the predictive impact of linguistic self-efficacy on SRL writing strategies, and profile differences in SRL writing strategies may caution teachers against taking a one-size-fits-all approach to boost students' writing self-efficacy to increase their use of SRL writing techniques. These results can also imply that educators should modify their methods to target the individual learning issues that students with various profiles might experience.

For example, to boost the use of text revision, interest augmentation, and collaborative learning, teachers should assist students with the Low on All Self-efficacy profile in strengthening their self-regulatory and learning environment self-efficacy. On the other hand, teachers could attempt to help students who fall into the Average on All Self-efficacy Medium and High on All Self-efficacy profiles maintain their present writing self-efficacy level to support their use of SRL writing strategies. Additionally, people who fit into the Low on All Self-efficacy and High on All Self-efficacy profiles might be given extra guidance. It might be suggested that they adjust their self-efficacy in classroom performance because either a high or low level of self-efficacy could have a major detrimental impact on how they handle feedback.

There might be certain restrictions that need to be noted. First of all, it should be mentioned that beginning and intermediate L2 learners, not advanced ones, were the primary participants in this study. Therefore, it is not possible to apply the findings of the current study to those advanced learners. To validate the findings of the current study, researchers may be encouraged to include advanced L2 learners in further research. Second, only an argumentative writing task was used to assess the learners' writing proficiency; as a result, it was unable to fully capture the range of writing proficiency. To determine whether the profile variations in the SRL writing techniques and writing self-efficacy predictive impacts on writing success remain constant across various writing assignments, it may be advised that researchers include additional writing tasks (such as narrative and expositive writing). Thirdly, we recommend that researchers employ information from other sources (such as stimulated interviews) to confirm the writing self-efficacy profiles found in the current study, given the inherent limitations of self-reported questionnaires.

REFERENCES

[1] Kong, S. C., & Yang, Y. (2024). A Human-Centred Learning and Teaching Framework Using Generative Artificial Intelligence for Self-Regulated Learning Development through Domain Knowledge Learning in K–12 Settings. IEEE Transactions on Learning Technologies.

[2] Lai, J. W. (2024). Adapting Self-Regulated Learning in an Age of Generative Artificial Intelligence Chatbots. Future Internet, 16(6), 218.

[3] Dahri, N. A., Yahaya, N., Al-Rahmi, W. M., Aldraiweesh, A., Alturki, U., Almutairy, S., ... & Soomro, R. B. (2024). Extended TAM based acceptance of AI-Powered ChatGPT for supporting metacognitive self-regulated learning in education: A mixed-methods study. Heliyon, 10(8).

[4] Liaqat, A., Munteanu, C., & Demmans Epp, C. (2021). Collaborating with mature English language learners to combine peer and automated feedback: A user-centered approach to designing writing support. International Journal of Artificial Intelligence in Education, 31(4), 638-679.

[5] Wei, L. (2023). Artificial intelligence in language instruction: impact on English learning achievement, L2 motivation, and self-regulated learning. Frontiers in Psychology, 14, 1261955.

[6] Tsai, Y. S., & Martinez-Maldonado, R. (2022). Human-centered approaches to data-informed feedback. In Handbook of Learning Analytics (pp. 213-222). Society for Learning Analytics Research.

[7] Moos, D. C., & Ringdal, A. (2012). Self-Regulated Learning in the Classroom: A Literature Review on the Teacher's Role. Education Research International, 2012(1), 423284.

[8] Paris, S. G., & Newman, R. S. (1990). Development aspects of self-regulated learning. Educational psychologist, 25(1), 87-102.

[9] Alonso-Mencía, M. E., Alario-Hoyos, C., Maldonado-Mahauad, J., Estévez-Ayres, I., Pérez-Sanagustín, M., & Delgado Kloos, C. (2020). Self-regulated learning in MOOCs: lessons learned from a literature review. Educational Review, 72(3), 319-345.
[10] Alibeigi, M., Davoudi, M., Ghaniabadi, S., & Amirian, M. R. (2024). Enhancing Students' Online Self-Regulation through Learning Analytics: Students' Expectations. Technology Assisted Language Education, 1-21.
[11] Gharahighehi, A., Van Schoors, R., Topali, P., & Ooge, J. (2024). Supporting Personalized Lifelong Learning with Human-Centered Artificial Intelligence Systems.
[12] Desai, S., & Chin, J. (2023, April). OK Google, let's learn: Using voice user interfaces for informal self-regulated learning of health topics among younger and older adults. In Proceedings of the 2023 CHI conference on human factors in computing systems (pp. 1-21).
[13] Buckingham Shum, S., Ferguson, R., & Martinez-Maldonado, R. (2019). Human-centred learning analytics. Journal of Learning Analytics, 6(2), 1-9.
[14] Drion, W. R. B. (2018). Online support system of personalized learning strategies: an application to promote self-regulated learning (Bachelor's thesis, University of Twente).
[15] Guesmi, M., Chatti, M. A., Tayyar, A., Ain, Q. U., & Joarder, S. (2022). Interactive visualizations of transparent user models for self-actualization: A human-centered design approach. Multimodal Technologies and Interaction, 6(6), 42.
[16] Nguyen, A. (2025). Human-AI Shared Regulation for Hybrid Intelligence in Learning and Teaching: Conceptual Domain, Ontological Foundations, Propositions, and Implications for Research.
[17] Azevedo, R., Millar, G. C., Taub, M., Mudrick, N. V., Bradbury, A. E., & Price, M. J. (2017, March). Using data visualizations to foster emotion regulation during self-regulated learning with advanced learning technologies: a conceptual framework. In Proceedings of the seventh international learning analytics & knowledge conference (pp. 444-448).
[18] Bohrer, R. (2023, October). Centering Humans in the Programming Languages Classroom: Building a Text for the Next Generation. In Proceedings of the 2023 ACM SIGPLAN International Symposium on SPLASH-E (pp. 26-37).