International Journal of Evaluation and Research in Education (IJERE)
Vol. 15, No. 5, October 2026, pp. 4001~4013
ISSN: 2252-8822, DOI: 10.11591/ijere.v15i5.39318

Social emotional learning in artificial intelligence-driven education: a bibliometric and strengths, weaknesses, opportunities, and threats analysis

Fatin Syamilah Che Yob[1,2], Rita Wong Mee Mee[1,3], Emily Abd Rahman[1], Lim Seong Pek[2,3], Wong Yee Von[4], Cathy Mae Toquero[5,6], Karen Joy B. Talidong[7]
[1]Centre for Language, National Defence University of Malaysia, Kuala Lumpur, Malaysia
[2]Faculty of Education and Liberal Arts, INTI International University Malaysia, Negeri Sembilan, Malaysia
[3]Faculty of Education, Shinawatra University, Pathum Thani, Thailand
[4]Faculty of Education and Social Sciences, Universiti Selangor, Selangor, Malaysia
[5]College of Education, Mindanao State University, General Santos City, Philippines
[6]Faculty of Psychology, Universitas Negeri Malang, Malang, Indonesia
[7]College of Teacher Education, Sultan Kudarat State University-ACCESS Campus, Tacurong City, Philippines

Article Info

Article history:

Received Mar 3, 2026
Revised May 24, 2026
Accepted Jun 26, 2026

Keywords:

AI-enhanced learning
Digital learning environments
Educational technology
Emotional analytics
Social emotional learning

ABSTRACT

The rapid integration of artificial intelligence (AI) into education has transformed how social emotional learning (SEL) is conceptualized, yet a comprehensive understanding of it is research trajectory and strategic implications remains limited. This study addresses this gap by examining influential SEL research within AI-driven educational contexts. A mixed analytical approach was employed, combining bibliometric performance analysis and strengths, weaknesses, opportunities, threats (SWOT) analysis. Using the Scopus database, publications from 2016-2025 were systematically identified according to PRISMA procedures, and the 10 most-cited articles were selected for in-depth evaluation. The findings reveal three dominant research orientations: critical policy discourse, pedagogical integration of SEL, and emerging AI-driven innovations. The SWOT analysis highlights strengths in AI-enabled personalization and engagement, as well as opportunities for adaptive emotional learning environments. However, weaknesses related to limited empirical validation and threats concerning ethical risks, emotional surveillance, and algorithmic bias persist. The study concludes that while AI presents transformative potential for SEL, its implementation must remain human-centered and ethically grounded. These findings offer important implications for educators, policymakers, and future research in developing responsible AI-supported SEL frameworks.

Corresponding Author:

Rita Wong Mee Mee
Centre for Language, National Defence University of Malaysia
Sungai Besi Camp, Sungai Besi, 57000, Kuala Lumpur, Malaysia
Email: ritawong@upnm.edu.my

1. INTRODUCTION

Social emotional learning (SEL) has gained increasing prominence as education systems respond to rapid digital transformation and the expanding integration of artificial intelligence (AI) in teaching and learning. AI technologies are reshaping how knowledge is delivered, monitored, and assessed [1], [2]. Traditionally, SEL has focused on developing emotional regulation, empathy, collaboration, and responsible decision-making through human interaction. However, these competencies are now cultivated in digitally mediated, algorithmically structured environments. As AI becomes embedded in everyday classroom practice, education is evolving into a sociotechnical ecosystem where both cognitive growth and emotional engagement are influenced by data-driven systems [3], [4]. Therefore, SEL must be reconceptualized not only as an interpersonal framework but also as a construct shaped by digital infrastructures that influence learners' affective and social experiences [5].

Exploring SEL in the AI era is essential because it offers a means to humanize increasingly automated educational processes. AI-powered systems can deliver personalized feedback, predictive insights, and adaptive learning pathways that enhance motivation, engagement, and self-regulation [6], [7]. Advances in affective computing further enable educational technologies to recognize learners' emotional states and dynamically adapt instructional responses, thereby strengthening emotional engagement, persistence, and personalized learning experiences [8], [9]. Research in AI-supported online and language learning contexts shows that emotionally responsive environments can improve learners' confidence, interaction quality, and sustained engagement [10], [11]. These developments position SEL as a central component of future-oriented education that aligns technological innovation with holistic human development.

Despite these benefits, integrating SEL within AI-driven systems introduces significant conceptual, pedagogical, and ethical concerns. The increasing datafication of emotional behaviors raises significant concerns about privacy, surveillance, and algorithmic bias in AI-mediated educational environments [12]. Converting emotional competencies into measurable analytics may oversimplify complex psychological and socio-emotional processes that resist reduction into algorithmic indicators [13]. Furthermore, many AI applications continue to lack longitudinal validation and teacher-centered implementation strategies, creating persistent gaps between technological innovation and sustainable classroom practice [14].

Considering these intersecting strengths and risks, a comprehensive analytical framework is necessary. Despite the growing body of literature on AI in education and SEL, current studies remain fragmented across conceptual, empirical, and technological domains. Existing research often focuses either on theoretical critiques of datafication or on isolated technological applications, with limited integration between these perspectives [12]. Moreover, there is a lack of comprehensive synthesis that combines quantitative mapping of influential scholarship with strategic evaluation of its practical and ethical implications [15]. This gap limits a holistic understanding of how AI-driven SEL is evolving and how it can be responsibly implemented in educational systems. Addressing this gap is crucial, as education stakeholders increasingly adopt AI technologies without clear alignment to pedagogical, ethical, and socio-emotional considerations.

Hence, this study offers significant contributions to multiple stakeholders within the educational ecosystem. For educators, the findings provide insights into how AI can be meaningfully integrated into SEL to enhance student engagement, emotional regulation, and personalized learning experiences without compromising human interaction. For policymakers, the study highlights critical ethical concerns, including data privacy, emotional surveillance, and algorithmic bias, thereby informing the development of regulatory frameworks for the responsible implementation of AI in education. For researchers, this study advances methodological innovation by combining bibliometric analysis with strengths, weaknesses, opportunities, threats (SWOT) evaluation, offering a replicable approach for synthesizing both quantitative trends and qualitative strategic insights. Collectively, the study supports the development of ethically grounded, pedagogically aligned, and future-ready AI-supported SEL frameworks.

This study contributes to the field by integrating bibliometric performance analysis with a strategic SWOT framework to provide a comprehensive, evidence-informed, and policy-relevant understanding of AI-driven SEL research. Through this combined analytical approach, the study seeks to systematically examine how SEL has evolved within the AI technology era by identifying the most influential publications shaping the field based on citation performance, while also critically evaluating the strengths, weaknesses, opportunities, and threats that characterize current SEL research within AI-supported educational contexts.

2. METHOD

This study employs a combined methodological design that integrates bibliometric performance analysis with a SWOT framework to examine influential scholarship on SEL in the AI technology era. Bibliometric analysis is widely regarded as a systematic and transparent approach for mapping knowledge structures, identifying research trends, and assessing scholarly impact across interdisciplinary domains [15], [16]. In rapidly developing areas such as AI in education (AIED), bibliometric techniques are particularly valuable for detecting influential publications, thematic concentrations, and key intellectual shifts [17], [18]. Large-scale reviews of AI in education further highlight citation-based performance mapping as an essential step for understanding research development, dominant narratives, and emerging [16], [19].

Using citation impact as the primary selection criterion, this study identifies the 10 most-cited articles that represent foundational, highly influential contributions at the intersection of SEL and AI. The analysis focuses on documents rather than authors or journals, consistent with contemporary bibliometric practices that prioritize conceptual influence and knowledge diffusion over productivity indicators [20], [21]. This ensures that field-defining works are selected based on their demonstrated theoretical and scholarly resonance within AI-mediated education research [22].

Following document selection, a qualitative SWOT framework is applied to systematically evaluate each article. SWOT analysis has increasingly been adopted in higher education and educational technology research as a strategic tool for examining innovation, governance, and digital transformation processes [23], [24]. Within AI-related scholarship, such approaches are particularly valuable for assessing ethical risks, policy implications, and long-term sustainability in technology-mediated learning environments [25]. Given the sensitivity of emotional data and algorithmic decision-making in SEL contexts, this dual-method approach enables both quantitative mapping and critical evaluation, offering a comprehensive and strategically grounded analysis of the field.

The selection of the top 10 most-cited documents was based on citation counts within the Scopus database, ensuring representation of influential and widely recognized contributions in the field. For the SWOT analysis, each selected article was systematically reviewed and coded according to recurring themes related to strengths, weaknesses, opportunities, and threats. The coding process involved iterative reading and thematic categorization to ensure consistency across studies. To enhance reliability, cross-validation was conducted among the authors to refine category definitions and ensure alignment in interpretation.

2.1. Search strategy

The study applied predefined inclusion criteria, as shown in Table 1, to ensure systematic and transparent article selection. The Scopus database was chosen due to its broad coverage of peer-reviewed educational and interdisciplinary research [16], [20]. Searches were conducted within the TITLE-ABS-KEY fields to capture studies explicitly addressing SEL and AI or technology-related contexts. The time frame was limited to publications from 2016 to 2025 to reflect contemporary developments in AI-driven education. Only journal articles written in English were included to maintain scholarly quality and comparability. The search string combined variations of SEL with AI and technology keywords, ensuring relevance and consistency across retrieved records.

The PRISMA flowchart, as shown in Figure 1, illustrates a systematic, transparent process for selecting articles. Initially, 761 records were identified through the Scopus database. After applying the publication year criterion (2016-2025), 232 records were removed. Screening by document type excluded 260 non-research articles, leaving 269 studies for eligibility assessment. Full-text evaluation further excluded 27 articles due to language limitations and scope misalignment. The final dataset comprised 242 studies, ensuring methodological rigor and relevance to the research objectives. This structured filtering process minimized bias while maintaining consistency between the search strategy and analytical framework, strengthening the reliability of subsequent bibliometric and SWOT analyses.

Table 1. Inclusion criteria for bibliometric analysis

Scopus database	ALL
Time period	2016 to 2025
Search field	TITLE-ABS-KEY
Search keywords	“socio-emotional OR social emotional OR SEL” AND “artificial intelligence OR AI OR technology”
Document types	Article
Language	English

2.2. Procedures

The study followed a systematic multi-phase procedure to ensure transparency and replicability. First, relevant articles were retrieved from the Scopus database using predefined search strings applied to the TITLE-ABS-KEY fields. The search was limited to English-language journal articles published between 2016 and 2025. Second, the retrieved records were screened using PRISMA procedures, including duplicate removal, filtering by document type, and full-text eligibility assessment, to ensure alignment with the study's focus on SEL in AI-related contexts. Third, citation analysis was conducted to identify the 10 most influential documents based on total citations. This criterion was adopted to ensure that selected articles represent high-impact and field-defining contributions. Fourth, qualitative coding was conducted using the SWOT framework. Each article was systematically analyzed to identify recurring themes related to strengths, weaknesses, opportunities, and threats. Coding was performed iteratively, allowing categories to emerge and stabilize through repeated comparison across studies.

To enhance reliability, cross-validation was conducted among the research team. Discrepancies in coding were discussed and resolved through consensus, ensuring consistency and interpretive alignment. This structured procedure strengthens the methodological rigor and transparency of the study.

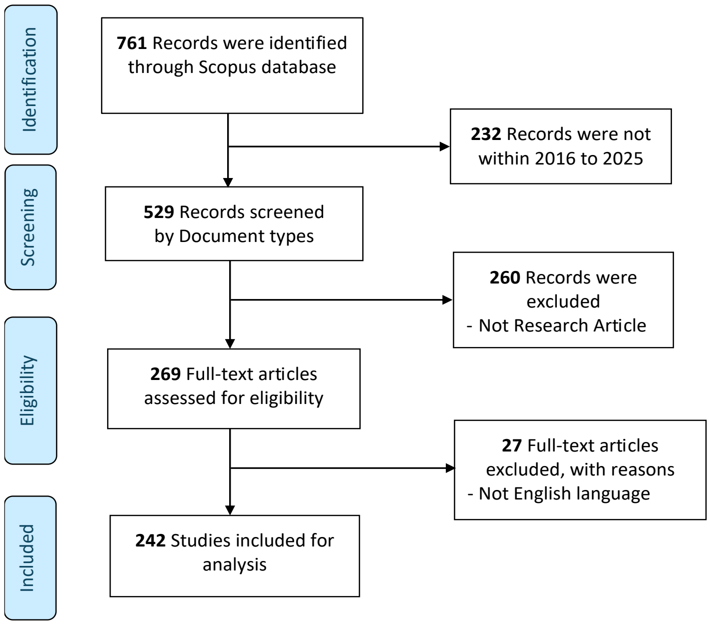

Figure 1. PRISMA flowchart

3. RESULTS AND DISCUSSION

3.1. Performance analysis

The bibliometric analysis identified 10 highly cited documents as shown in Table 2 that collectively shape scholarly discourse on SEL in technology-mediated environments. The selection of the top ten articles was based on absolute citation counts within the Scopus database at the time of data extraction, ensuring that only highly influential and widely recognized studies were included. Citation counts range from 64 to 130, indicating sustained academic influence across interdisciplinary domains. The most cited study, Williamson [26], critically examines persuasive educational technologies and highlights how digital platforms operationalize SEL through behavioral governance. Subsequent works by Williamson and Piattoeva [27] and Williamson [28] further extend this discussion by analyzing datafication, standardization, and psychometric infrastructures underlying SEL measurement.

Table 2. Top 10 most cited documents

No.	Author(s)	Title	No. of citations
1.	Williamson [26]	Decoding ClassDojo: psycho-policy, social-emotional learning and persuasive educational technologies	130
2.	Williamson and Piattoeva [27]	Objectivity as standardization in data-scientific education policy, technology and governance	87
3.	Williamson [28]	Psychodata: disassembling the psychological, economic, and statistical infrastructure of ‘social-emotional learning’	82
4.	Elmi [29]	Integrating social emotional learning strategies in higher education	75
5.	Allen *et al.* [30]	From quality to outcomes: a national study of afterschool STEM programming	73
6.	Sethi and Jain [10]	AI technologies for social emotional learning: recent research and future directions	68
7.	Zong and Yang [11]	How AI-enhanced social–emotional learning framework transforms EFL students' engagement and emotional well-being	64
8.	Guettala *et al.* [31]	Generative artificial intelligence in education: advancing adaptive and personalized learning	59
9.	Garner *et al.* [32]	Innovations in science education: infusing social emotional principles into early STEM learning	54
10.	Walker and Weidenbenner [33]	Social and emotional learning in the age of virtual play: technology, empathy, and learning	52

Empirical and pedagogical contributions are represented by Elmi [29] and Allen *et al.* [30], which demonstrate the effectiveness of SEL integration in higher education and STEM learning contexts. Recent publications increasingly emphasize the applications of AI, particularly Sethi and Jain [10] and Zong and Yang [11], reflecting a shift toward AI-enhanced emotional learning and learner engagement. Interestingly, several highly cited studies originate in broader technological or engineering domains, indicating that interdisciplinary citation diffusion extends beyond education research.

The findings reveal three dominant research orientations: critical policy analysis, pedagogical implementation of SEL, and emerging AI-driven innovation. This distribution suggests that while foundational theoretical critiques remain influential, contemporary research trends are moving toward applied AI-supported SEL frameworks and technologically responsive learning environments.

The overlay visualization in Figure 2 reveals the temporal development of research themes related to SEL in technology-mediated education. Earlier publications concentrated on digital learning environments and foundational SEL integration, reflecting initial explorations of technology-supported emotional development [33]. More recent studies, indicated by warmer color gradients, increasingly emphasize AI, adaptive systems, and data-driven personalization in learning contexts [10], [11].

This shift demonstrates a growing scholarly transition from general educational technology toward AI-enabled emotional analytics and intelligent learning environments, signaling an emerging research focus on technologically enhanced socio-emotional development. These findings indicate a clear shift in SEL research from predominantly theoretical and policy-oriented discourse toward applied, technology-integrated approaches. The growing presence of AI-focused research suggests the field is evolving toward practical application, though theoretical critiques continue to shape its ethical and conceptual foundations.

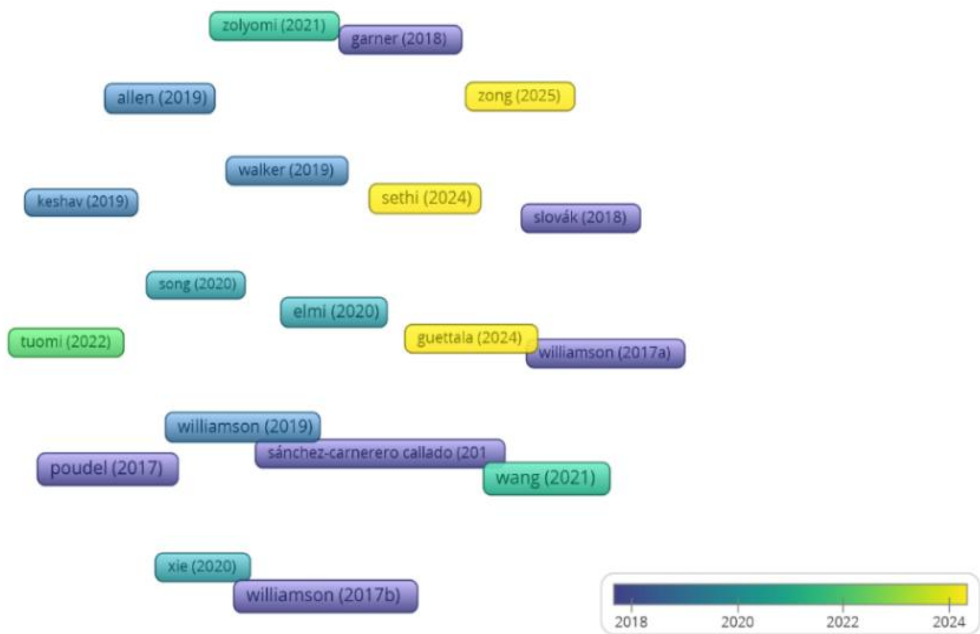

Figure 2. Overlay visualization (VOSviewer)

3.2. SWOT analysis

To provide a deeper interpretation beyond citation performance, a SWOT analysis was conducted to critically evaluate the strengths, weaknesses, opportunities, and threats emerging from the most influential studies on SEL in the AI technology era. This analytical approach enables systematic examination of both internal research characteristics and external developments shaping the field. By synthesizing conceptual, empirical, and technological perspectives identified in the selected literature, the SWOT Matrix as shown in Table 3 highlights current contributions, existing limitations, future research potential, and ethical challenges. The following subtopics present a thematic discussion derived from cross-study patterns observed across the analyzed publications.

Table 3. SWOT matrix

No.	Article	Strengths (S)	Weaknesses (W)	Opportunities (O)	Threats (T)
1	[26]	Deep theoretical critique of edtech governance; reveals psychological influence of platforms	Conceptual; lacks empirical classroom validation	Guides ethical AI-SEL design frameworks	Risk of surveillance capitalism and behavioral manipulation
2	[27]	Strong policy-level insight into algorithmic governance	Limited pedagogical application discussion	Supports development of responsible AI governance models	Over-standardization may reduce emotional individuality
3	[28]	Reveals hidden statistical and economic systems behind SEL analytics	Highly theoretical; complex for practitioners	Opens interdisciplinary research between psychology, AI, and education	Commodification of student emotions through data extraction
4	[29]	Practical pedagogical strategies; adaptable across disciplines	Not AI-focused; limited technological discussion	Foundation for AI-supported SEL interventions	Implementation variability across institutions
5	[30]	Large-scale empirical dataset; strong outcome validation	Technology role indirect	Evidence base for AI-driven STEM-SEL environments	Resource dependency for scaling programs
6	[10]	Current overview of AI tools; future research directions	Limited empirical testing	Framework for AI-SEL innovation and system development	Ethical risks and algorithm bias
7	[11]	Empirical evidence linking AI with engagement and emotional well-being	Context-specific (EFL); generalizability limited	Expansion into language education and adaptive emotional learning	Overreliance on AI mediation may weaken human interaction
8	[31]	Strong technological explanation; personalization potential	SEL implications implicit rather than central	Integration of emotional analytics into adaptive learning	Data privacy and emotional profiling concerns
9	[32]	Early integration model connecting cognition and emotion	Pre-AI era technological framing	Basis for AI-supported early childhood SEL design	Teacher readiness challenges
10	[33]	Explores empathy and social interaction via technology	Small-scale conceptual discussion	Development of immersive AI/VR SEL environments	Reduced real-world social skill transfer

3.2.1. Strengths

a. Integration of SEL with emerging educational technologies

A major strength identified across the literature is the increasing integration of social-emotional learning with digital and AI-enabled educational environments. Studies demonstrate that technology platforms can support emotional awareness, engagement, and adaptive feedback mechanisms, thereby enhancing learning outcomes. AI systems enable personalized emotional support by analyzing learner interaction patterns and behavioral data, improving responsiveness compared to traditional instruction. Empirical findings show improved engagement and emotional well-being when AI-enhanced frameworks are applied, particularly in language learning and virtual environments [11], [33]. These developments position AI as a scalable mechanism for embedding SEL into diverse educational contexts.

b. Strong theoretical and policy foundations for SEL development

The field benefits from robust theoretical grounding that examines psychological governance, data infrastructures, and the policy implications of SEL technologies. Critical scholarship has clarified how digital platforms operationalize emotional competencies through measurable indicators, providing conceptual clarity for future research. Such analyses deepen understanding of how educational technologies shape learner behavior and institutional decision-making [26], [28]. Policy-oriented discussions also highlight the growing role of data science in education governance, offering structured frameworks for standardization and accountability [27]. These theoretical contributions strengthen the legitimacy of SEL research within broader educational transformation discourse.

c. Empirical evidence supporting SEL outcomes across disciplines

Several studies provide empirical validation linking SEL integration with positive academic and developmental outcomes. Large-scale investigations in STEM and higher education contexts demonstrate improved collaboration, persistence, and learner motivation when SEL principles are embedded into instructional design [30], [29]. Early STEM education research further shows that emotional competencies enhance cognitive learning processes and engagement in scientific inquiry [32]. This empirical support establishes SEL not merely as a psychological construct but as a measurable contributor to educational performance, strengthening arguments for AI-supported SEL implementation across disciplines.

3.2.2. Weaknesses

a. Limited empirical validation of AI-Driven SEL systems

Despite rapid technological advancement, many AI-SEL studies remain conceptual or exploratory rather than experimentally validated. Reviews of AI applications emphasize potential benefits but acknowledge insufficient longitudinal or large-scale empirical testing [10]. Early critical works also focus primarily on theoretical critique rather than classroom implementation [26]. As a result, evidence demonstrating sustained emotional development outcomes remains limited. This methodological imbalance creates uncertainty regarding real-world effectiveness and scalability, suggesting that the field is still transitioning from conceptual innovation toward evidence-based pedagogical practice.

b. Fragmentation between technological innovation and pedagogical practice

Another weakness lies in the disconnect between technological development and classroom pedagogy. AI research often prioritizes personalization algorithms and adaptive systems while overlooking instructional integration and teacher roles [31]. Conversely, pedagogical SEL studies frequently lack technological sophistication [29]. This separation results in parallel research trajectories rather than cohesive interdisciplinary models. Without alignment between educators, psychologists, and AI developers, implementation risks becoming technologically driven rather than pedagogically meaningful, limiting the practical impact of AI-enabled SEL initiatives.

c. Overreliance on datafication and quantification of emotions

The increasing measurement of emotional competencies through digital analytics introduces methodological and philosophical limitations. Scholars warn that transforming emotional development into quantifiable indicators may oversimplify complex human experiences [28]. Standardized emotional metrics risk privileging measurable behaviors over authentic emotional growth [27]. Such reductionism may constrain culturally responsive interpretations of emotion and learning, raising concerns about whether AI systems can adequately capture contextual and relational aspects central to SEL development.

3.2.3. Opportunities

a. Personalized and adaptive emotional learning through AI

AI technologies create opportunities for individualized SEL pathways through adaptive feedback, predictive analytics, and generative learning environments. Personalized systems can adjust instructional strategies based on emotional states and engagement patterns, thereby supporting differentiated learning experiences [31]. Emerging frameworks demonstrate how AI-enhanced environments improve learner engagement and emotional regulation, particularly in language education settings [11]. These innovations suggest the potential emergence of emotionally intelligent learning ecosystems capable of supporting diverse learner needs at scale.

b. Expansion of SEL into new learning modalities and contexts

Technological advances enable SEL implementation beyond traditional classrooms, including virtual play, online collaboration, and hybrid learning environments. Digital platforms foster empathy, communication, and social interaction across geographically distributed learners [33]. AI-supported environments also allow integration of SEL into STEM, higher education, and lifelong learning contexts [29], [30]. This expansion supports global accessibility and aligns SEL with future-ready competencies required in digitally mediated societies.

3.2.4. Threats

a. Ethical risks and emotional surveillance

A critical threat emerging from the literature involves ethical concerns surrounding emotional data collection and surveillance. AI systems capable of monitoring behavioral and affective indicators may inadvertently enable psychological profiling or commercial exploitation of student data [26], [28]. The commodification of emotional information raises questions about consent, autonomy, and student privacy. Without ethical safeguards, SEL technologies risk reinforcing power imbalances between institutions, technology providers, and learners.

b. Algorithmic bias and loss of human-centered learning

AI-driven SEL systems may reproduce biases embedded within training datasets or algorithmic assumptions. Standardized emotional models may fail to represent cultural diversity or individual emotional expression, potentially marginalizing learners [10]. Additionally, excessive reliance on automated emotional feedback may reduce authentic teacher-student relationships, which remain central to socio-emotional development [32]. This shift risks transforming SEL into a technologically mediated process rather than a relational educational experience grounded in human interaction.

3.3. Discussion

The integration of bibliometric performance analysis and SWOT evaluation offers meaningful insights into the development of SEL research in the AI technology era. Document-level citation patterns reveal that influential scholarship continues to be shaped by critical examinations of governance, policy, and sociotechnical dimensions of AI in education [4]. Highly cited studies foreground concerns about datafication, algorithmic governance, and digital surveillance, highlighting how AI systems increasingly construct and regulate learners' emotional and behavioral identities within digital learning ecosystems [13], [34]. The prominence of such work suggests sustained academic attention to the ethical and political implications of measuring and standardizing emotional competencies through data-driven infrastructures.

Concurrently, empirical research underscores the instructional benefits of integrating SEL within AI-supported learning environments. Evidence indicates that adaptive systems and personalized feedback mechanisms can strengthen engagement, motivation, and self-regulated learning processes [35], [36]. Studies in higher education and STEM contexts further demonstrate that socially and emotionally responsive designs enhance academic persistence and collaborative outcomes in digitally mediated settings [37]. These findings reinforce the role of SEL as essential for sustaining learner well-being and meaningful participation in AI-enhanced education.

The SWOT analysis portrays a field in transition, balancing technological promise with ethical vigilance. Strengths include AI's capacity for personalization and affect-sensitive feedback, supported by advances in emotion-aware computing and adaptive learning analytics [8], [9], while opportunities are evident in online and intelligent language learning contexts that promote interactive engagement [10], [11]. Nevertheless, weaknesses such as limited longitudinal evidence and gaps in teacher preparedness persist [2], [3]. Ethical risks remain pressing concerns as AI integration expands within emotionally sensitive educational domains [34]. Overall, SEL scholarship appears to be evolving toward the integration of applied AI, requiring careful alignment among innovation, ethics, and human-centered pedagogy.

The implications of these findings are significant for both research and practice. For researchers, the study highlights the need for more longitudinal and empirically validated investigations into AI-supported SEL to strengthen evidence-based implementation. For educators, the findings emphasize the importance of integrating AI tools in ways that support, rather than replace, human interaction and emotional development [20]. For policymakers, the study underscores the urgency of establishing ethical guidelines and governance frameworks to regulate the use of emotional data in AI-driven learning environments. Moving forward, future research should prioritize interdisciplinary collaboration, combining insights from education, psychology, and AI to develop holistic and sustainable SEL models.

From a practical perspective, these findings suggest that integrating AI into SEL must prioritize human-centered pedagogical design. Educators should adopt AI tools that support emotional engagement without diminishing interpersonal interaction. Institutions are encouraged to invest in teacher training programs that enhance digital and emotional pedagogical competencies. Furthermore, policymakers must establish clear ethical guidelines governing the use of emotional data, ensuring transparency, data protection, and equitable access. These actionable directions highlight the need for a balanced approach that integrates technological innovation with educational integrity.

3.3.1. Theoretical implications

This study makes a theoretical contribution by integrating bibliometric performance analysis with a SWOT framework to examine SEL within the evolving landscape of AI in education. By combining citation-based mapping with strategic qualitative evaluation, the study responds to emerging methodological perspectives that advocate integrative analytical approaches capable of capturing both intellectual influence and thematic development across complex educational technology domains [38], [39]. Such hybrid approaches enable researchers to move beyond descriptive trend identification toward a deeper interpretive understanding of how knowledge structures evolve within rapidly advancing research fields.

The findings reposition AI not merely as a pedagogical support tool but as a broader socio-technical system embedded within processes of digital governance, algorithmic decision-making, and platform-based educational infrastructures [40], [41]. This perspective reflects a conceptual transition from traditional human-centered SEL models toward data-informed emotional learning environments shaped by intelligent tutoring systems, learning analytics, and emotion-aware computational designs [42], [43]. Within such environments, emotional engagement becomes increasingly mediated through computational interpretation and adaptive feedback mechanisms.

By identifying both strengths and threats, the study advances understanding of how AI-driven personalization can enhance learner engagement, motivation, and self-regulated learning through responsive instructional systems [44], [45]. At the same time, the analysis highlights growing concerns regarding surveillance practices, algorithmic bias, and the datafication of emotional experiences within digitally mediated learning ecosystems [46]. Overall, the findings encourage the development of interdisciplinary frameworks that integrate AI ethics, learning sciences, and socio-emotional development to ensure that technological innovation remains aligned with human-centered educational values and sustainable pedagogical practice.

3.3.2. Practical implications

In practice, the findings offer actionable guidance for educators, policymakers, and technology developers seeking to implement AI-supported SEL in responsible, pedagogically meaningful ways. Recent studies indicate that AI-enabled adaptive learning environments can enhance learner engagement and support personalized learning pathways when intentionally embedded within sound instructional design frameworks [47], [48]. At the same time, research highlights that AI should augment rather than replace teacher-student relationships, preserving the interpersonal and relational foundations essential for socio-emotional development and meaningful learning experiences [49], [50]. In AI-supported language learning and online education contexts, emotionally responsive digital systems have demonstrated potential to improve participation, interaction quality, and learner collaboration through adaptive feedback and affect-aware interaction design [51].

These developments provide institutions with opportunities to design adaptive learning environments that foster emotional engagement alongside academic achievement. At the same time, documented risks associated with datafication, surveillance, and algorithmic bias emphasize the importance of strong ethical governance in AI-enabled education systems [40]. Policymakers should therefore establish transparent regulatory and governance frameworks that safeguard the privacy of emotional data while ensuring equitable and culturally responsive AI implementation. For practitioners, sustained professional learning and capacity building remain essential to support effective [47], human-centered integration of AI within SEL-oriented pedagogical practice.

At the policy level, governments and educational authorities should prioritize developing national guidelines for ethical AI use in education, particularly regarding the governance of emotional data. Policies should address issues of data ownership, consent, transparency, and algorithmic accountability. Additionally, funding initiatives should support the development of culturally responsive AI systems that reflect diverse learner profiles. These policy-level interventions are essential to ensure that AI-driven SEL contributes to equitable and sustainable educational transformation.

4. CONCLUSION

This study examined the development of SEL in the AI era through a combined bibliometric performance analysis and SWOT analysis. By analyzing the top ten most cited documents, the findings reveal that SEL research has evolved from critical discussions of datafication and educational governance toward emerging applications of AI to support emotional engagement and personalized learning. The SWOT analysis further demonstrates that while AI offers significant strengths and opportunities, important weaknesses and threats remain, including limited empirical validation, ethical concerns, and risks related to the surveillance of emotional data.

The study highlights the need to balance technological innovation with human-centered pedagogy. AI should function as an enabling tool that enhances socio-emotional development rather than replacing authentic interpersonal learning experiences. The integration of ethical considerations and pedagogical alignment is therefore essential for sustainable implementation. Despite it is contributions, this study has several limitations. The analysis was restricted to the Scopus database and focused only on the top ten most-cited documents, which may not fully represent the diversity of emerging research in the field. Additionally, the qualitative nature of SWOT analysis may introduce interpretive bias despite efforts to ensure consistency. Future studies are encouraged to expand dataset sources and incorporate mixed-method validation approaches.

Importantly, the findings contribute to sustainable development goal 4 (quality education) by emphasizing inclusive, equitable, and holistic learning environments that support both cognitive and emotional development. Advancing SEL through responsible AI integration can help prepare learners with the social competencies required for future societies. Future research should continue developing ethically grounded, empirically validated AI-supported SEL frameworks that promote meaningful and sustainable educational transformation.

FUNDING INFORMATION

This work was supported by the National Defence University of Malaysia and INTI International University, Malaysia.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Fatin Syamilah Che Yob	✓	✓	✓		✓			✓	✓				✓	✓
Rita Wong Mee Mee		✓		✓		✓		✓		✓	✓			✓
Emily Abd Rahman	✓		✓			✓			✓		✓	✓	✓	
Lim Seong Pek	✓				✓		✓			✓		✓		
Wong Yee Von		✓			✓		✓			✓		✓		
Cathy Mae Toquero	✓			✓	✓		✓			✓				
Karen Joy B. Talidong		✓		✓		✓				✓	✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

REFERENCES

[1] O. Zawacki-Richter *et al.*, "Elements of open education: an invitation to future research," *The International Review of Research in Open and Distributed Learning*, vol. 21, no. 3, Mar. 2020, doi: 10.19173/irrodl.v21i3.4659.

[2] W. Holmes *et al.*, "Ethics of AI in education: towards a community-wide framework," *International Journal of Artificial Intelligence in Education*, vol. 32, no. 3, pp. 504–526, Sep. 2022, doi: 10.1007/s40593-021-00239-1.

[3] R. Luckin, M. Cukurova, C. Kent, and B. du Boulay, "Empowering educators to be AI-ready," *Computers and Education: Artificial Intelligence*, vol. 3, 2022, doi: 10.1016/j.caeai.2022.100076.

[4] B. Williamson and R. Eynon, "Historical threads, missing links, and future directions in AI in education," *Learning, Media and Technology*, vol. 45, no. 3, pp. 223–235, Jul. 2020, doi: 10.1080/17439884.2020.1798995.

[5] L. Pangrazio and N. Selwyn, "Towards a school-based 'critical data education,'" *Pedagogy, Culture and Society*, vol. 29, no. 3, pp. 431–448, May 2021, doi: 10.1080/14681366.2020.1747527.

[6] X. Chen, H. Xie, S. J. Qin, F. L. Wang, and Y. Hou, "Artificial intelligence-supported student engagement research: text mining and systematic analysis," *European Journal of Education*, vol. 60, no. 1, Mar. 2025, doi: 10.1111/ejed.70008.

[7] H. Khosravi *et al.*, "Explainable artificial intelligence in education," *Computers and Education: Artificial Intelligence*, vol. 3, 2022, doi: 10.1016/j.caeai.2022.100074.

[8] A. O. R. Vistorte, A. Deroncele-Acosta, J. L. M. Ayala, A. Barrasa, C. López-Granero, and M. Martí-González, "Integrating artificial intelligence to assess emotions in learning environments: a systematic literature review," *Frontiers in Psychology*, vol. 15, 2024, doi: 10.3389/fpsyg.2024.1387089.

[9] V. Farsadaki and C. Griffy-Brown, "AI affective computing and behavioral health," *Frontiers in Computer Science*, vol. 7, 2026, doi: 10.3389/fcomp.2025.1692728.

[10] S. S. Sethi and K. Jain, "AI technologies for social emotional learning: recent research and future directions," *Journal of Research in Innovative Teaching and Learning*, vol. 17, no. 2, pp. 213–225, Aug. 2024, doi: 10.1108/JRIT-03-2024-0073.

[11] Y. Zong and L. Yang, "How AI-enhanced social–emotional learning framework transforms EFL students' engagement and emotional well-being," *European Journal of Education*, vol. 60, no. 1, Mar. 2025, doi: 10.1111/ejed.12925.

[12] L. Bouakaz and S. Khalid, "AI in education: a sociological exploration of technology in learning environments," *Frontiers in Education*, vol. 10, Nov. 2025, doi: 10.3389/feduc.2025.1700876.

[13] S. Akgun and C. Greenhow, "Artificial intelligence in education: Addressing ethical challenges in K-12 settings," *AI and Ethics*, vol. 2, no. 3, pp. 431–440, 2022.

[14] K. Zhou, H. Deng, H. C. Chan, and C.-H. Lin, "Integrating generative AI into language teachers' professional development: a longitudinal study using the synthesis of qualitative data (SQD) model," *Professional Development in Education*, pp. 1–29, Nov. 2025, doi: 10.1080/19415257.2025.2586643.

[15] R. Zou, L. Jiang, and W. Wider, "Bibliometric insights into the open education landscape," *The International Review of Research in Open and Distributed Learning*, vol. 26, no. 1, pp. 283–309, Feb. 2025, doi: 10.19173/irrodl.v26i1.7953.

[16] B. Zhou, S. P. Lim, N. Kabir, M. Bouteraa, and A. Asna, "Artificial intelligence in mobile-interactive EFL learning environments," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 20, no. 08, Apr. 2026, doi: 10.3991/ijim.v20i08.59677.

[17] V. Maphosa and M. Maphosa, "Artificial intelligence in higher education: a bibliometric analysis and topic modeling approach," *Applied Artificial Intelligence*, vol. 37, no. 1, Dec. 2023, doi: 10.1080/08839514.2023.2261730.

[18] M. S. Prayuda, F. Y. A. Ginting, and L. Tamba, "Tracing two decades of artificial intelligence in education: a bibliometric analysis of trends, themes, and future directions (2000–2025)," *European Journal of Educational Research*, vol. 15, no. 1, pp. 285–304, Nov. 2025, doi: 10.12973/eu-jer.15.1.285.

[19] Z. Bo *et al.*, "Transforming translation education: a bibliometric analysis of artificial intelligence's role in fostering sustainable development," *International Journal of Learning, Teaching and Educational Research*, vol. 24, no. 3, pp. 166–190, Mar. 2025, doi: 10.26803/ijlter.24.3.9.

[20] W. Wider *et al.*, "Mapping the terrain of social-emotional learning: a bibliometric study on its past, present, and future," *School Mental Health*, vol. 17, no. 3, pp. 1097–1112, Sep. 2025, doi: 10.1007/s12310-025-09781-y.

[21] Z. Yang, S. Ge, A. N. Yahya, A. Y. Kamaruddin, P. Yang, and H. Zhang, "A bibliometric landscape of social-emotional learning publications over the past decades," *School Mental Health*, vol. 18, no. 1, pp. 1–24, Mar. 2026, doi: 10.1007/s12310-025-09828-0.

[22] W. Cong, L. S. Pek, Z. Yuchen, I. N. A. Latif, Z. Bo, and L. Ming, "Integrating generative AI in language education: a systematic review of pedagogical, ethical, and technological themes," *International Journal of Learning, Teaching and Educational Research*, vol. 25, no. 2, pp. 577–595, Feb. 2026, doi: 10.26803/ijlter.25.2.26.

[23] M. Farrokhnia, S. K. Banihashem, O. Noroozi, and A. Wals, "A SWOT analysis of ChatGPT: Implications for educational practice and research," *Innovations in Education and Teaching International*, vol. 61, no. 3, pp. 460–474, May 2024, doi: 10.1080/14703297.2023.2195846.

[24] F. Almasri, "Exploring the impact of artificial intelligence in teaching and learning of science: a systematic review of empirical research," *Research in Science Education*, vol. 54, no. 5, pp. 977–997, Oct. 2024, doi: 10.1007/s11165-024-10176-3.

[25] B. Jallali, S. Hafdhi, A. M. E. Aloufi, B. K. Masoudi, and A. M. Alshmrani, "Toward sustainable learning: a multidimensional framework of AI integration, engagement, and digital resilience in Saudi Higher Education," *Sustainability*, vol. 18, no. 2, p. 944, Jan. 2026, doi: 10.3390/su18020944.

[26] B. Williamson, "Decoding ClassDojo: psycho-policy, social-emotional learning and persuasive educational technologies," *Learning, Media and Technology*, vol. 42, no. 4, pp. 440–453, Oct. 2017, doi: 10.1080/17439884.2017.1278020.

[27] B. Williamson and N. Piattoeva, "Objectivity as standardization in data-scientific education policy, technology and governance," in *The Datafication of Education*, Routledge, 2020, pp. 81–93, doi: 10.4324/9780429341359-7.

[28] B. Williamson, "Psychodata: disassembling the psychological, economic, and statistical infrastructure of 'social-emotional learning,'" *Journal of Education Policy*, vol. 36, no. 1, pp. 129–154, Jan. 2021, doi: 10.1080/02680939.2019.1672895.

[29] C. Elmi, "Integrating social emotional learning strategies in Higher Education," *European Journal of Investigation in Health, Psychology and Education*, vol. 10, no. 3, pp. 848–858, Aug. 2020, doi: 10.3390/ejihpe10030061.

[30] P. J. Allen *et al.*, "From quality to outcomes: a national study of afterschool STEM programming," *International Journal of STEM Education*, vol. 6, no. 1, p. 37, Dec. 2019, doi: 10.1186/s40594-019-0191-2.

[31] M. Guettala, S. Bourekkache, O. Kazar, and S. Harous, "Generative artificial intelligence in education: advancing adaptive and personalized learning," *Acta Informatica Pragensia*, vol. 13, no. 3, pp. 460–489, Aug. 2024, doi: 10.18267/j.aip.235.

[32] P. W. Garner, N. Gabitova, A. Gupta, and T. Wood, "Innovations in science education: infusing social emotional principles into early STEM learning," *Cultural Studies of Science Education*, vol. 13, no. 4, pp. 889–903, Dec. 2018, doi: 10.1007/s11422-017-9826-0.

[33] G. Walker and J. Venker Weidenbenner, "Social and emotional learning in the age of virtual play: technology, empathy, and learning," *Journal of Research in Innovative Teaching and Learning*, vol. 12, no. 2, pp. 116–132, Aug. 2019, doi: 10.1108/JRIT-03-2019-0046.

[34] D. Nopas, "Algorithmic learning or learner autonomy? Rethinking AI's role in digital education," *Qualitative Research Journal*, Apr. 2025, doi: 10.1108/QRJ-11-2024-0282.

[35] Z. Ouyang, "Self-regulated learning and engagement as serial mediators between AI-driven adaptive learning platform characteristics and educational quality: a psychological mechanism analysis," *Frontiers in Psychology*, vol. 16, Oct. 2025, doi: 10.3389/fpsyg.2025.1646469.

[36] K. Sharma, A. Nguyen, and Y. Hong, "Self-regulation and shared regulation in collaborative learning in adaptive digital learning environments: A systematic review of empirical studies," *British Journal of Educational Technology*, vol. 55, no. 4, pp. 1398–1436, Jul. 2024, doi: 10.1111/bjet.13459.

[37] I. Finkelstein and S. Soffer-Vital, "Cultural empathy in AI-supported collaborative learning: advancing inclusive digital learning in higher education," *Education Sciences*, vol. 15, no. 10, p. 1305, Oct. 2025, doi: 10.3390/educsci15101305.

[38] M. Ali, M. Ma, M. Muneeb, and G. K. W. Wong, "Mapping contemporary AI-education intersections and developing an integrated convergence framework: a bibliometric-driven and inductive content analysis," *Metrics*, vol. 2, no. 4, p. 23, Nov. 2025, doi: 10.3390/metrics2040023.

[39] H. Chatti and M. Argoubi, "Artificial intelligence in knowledge management: identifying intellectual milestones and emerging domains," *Electronic Journal of Knowledge Management*, vol. 23, no. 2, pp. 122–148, Sep. 2025, doi: 10.34190/ejkm.23.2.4260.

[40] A. O. Alsuhaymi and F. A. Atallah, "Sustainable education in the age of artificial intelligence and digitalization: a value-critical approach," *Sustainability*, vol. 18, no. 3, p. 1257, Jan. 2026, doi: 10.3390/su18031257.

[41] R. Farrow, "The possibilities and limits of explicable artificial intelligence (XAI) in education: a socio-technical perspective," *Learning, Media and Technology*, vol. 48, no. 2, pp. 266–279, Apr. 2023, doi: 10.1080/17439884.2023.2185630.

[42] M. Alrabie, "Nurturing the future," in *Teaching with Artificial Intelligence*, London: Routledge, 2025, pp. 217–240, doi: 10.4324/9781003685241-18.

[43] H. Albasry, E. Carmona-Cejudo, A. Rauf, and D. Chen, "A systematically derived AI-based framework for student-centered learning in higher education," *Social Sciences and Humanities Open*, vol. 12, p. 102085, 2025, doi: 10.1016/j.ssaho.2025.102085.

[44] Q. Xu, Y. Liu, and X. Li, "Unlocking student potential: How AI-driven personalized feedback shapes goal achievement, self-efficacy, and learning engagement through a self-determination lens," *Learning and Motivation*, vol. 91, p. 102138, Aug. 2025, doi: 10.1016/j.lmot.2025.102138.

[45] H. Shafiee Rad, "Reinforcing L2 reading comprehension through artificial intelligence intervention: refining engagement to foster self-regulated learning," *Smart Learning Environments*, vol. 12, no. 1, p. 23, Mar. 2025, doi: 10.1186/s40561-025-00377-2.

[46] L. Gourlay, "Surveillance and datafication in higher education: documentation of the human," *Postdigital Science and Education*, vol. 6, no. 4, pp. 1039–1048, Dec. 2024, doi: 10.1007/s42438-022-00352-x.

[47] W. Strielkowski, V. Grebennikova, A. Lisovskiy, G. Rakhimova, and T. Vasileva, "AI-driven adaptive learning for sustainable educational transformation," *Sustainable Development*, vol. 33, no. 2, pp. 1921–1947, Apr. 2025, doi: 10.1002/sd.3221.

[48] L. Yan, A. Suleman Abdullah Alwabel, and U. H. Mohamad, "AI-powered education: transforming teacher-student interactions and advancing sustainable learning practices," *European Journal of Education*, vol. 60, no. 4, Dec. 2025, doi: 10.1111/ejed.70351.

[49] Q. Zhang and J. Fan, "Beyond Substitution: How teacher interpersonal behaviours empower students to communicate with AI—a dual-mediation model of enjoyment and trust," *European Journal of Education*, vol. 61, no. 1, Mar. 2026, doi: 10.1111/ejed.70499.
[50] D. Henriksen, E. Creely, N. Gruber, and S. Leahy, "Social-emotional learning and generative AI: a critical literature review and framework for teacher education," *Journal of Teacher Education*, vol. 76, no. 3, pp. 312–328, May 2025, doi: 10.1177/00224871251325058.
[51] T. Xiao, S. Yi, and S. Akhter, "AI-supported online language learning: learners' self-esteem, cognitive-emotion regulation, academic enjoyment, and language success," *The International Review of Research in Open and Distributed Learning*, vol. 25, no. 3, pp. 77–96, Aug. 2024, doi: 10.19173/irrodl.v25i3.7666.

BIOGRAPHIES OF AUTHORS

Fatin Syamilah Che Yob is an English lecturer at the Faculty of Education and Liberal Arts, INTI International University. She specializes in TESL, social emotional learning, materials design, and gamified studies. She can be contacted at email: fatinsyamilah.cheyob@newinti.edu.my.

Rita Wong Mee Mee is a TESL lecturer at the Centre for Language at the National Defence University of Malaysia (NDUM). She is also a research fellow at Shinawatra University, Thailand. She received her Doctorate in Education (Ed.D) degree from Universiti Selangor. She specializes in materials development, game-based learning, and crisis communication. She can be contacted at email: ritawong@upnm.edu.my.

Emily Abd Rahman is the head of Department at the Centre for Language at the National Defence University of Malaysia (NDUM). She specialized in mobile learning and teaching English as a second language. She can be contacted at email: emily@upnm.edu.my.

Lim Seong Pek is a senior lecturer at the Faculty of Education and Liberal Arts, INTI International University. He is also a research fellow at Shinawatra University, Thailand. He received his Doctorate in Education (Ed.D) degree from Universiti Selangor. He specializes in media literacy, multimodality, and teacher education. He can be contacted at email: seongpek.lim@newinti.edu.my.

Wong Yee Von is a TESL lecturer at the Faculty of Education and Social Sciences, Universiti Selangor (UNISEL). She specialized in code-switching and gender study. She can be contacted at email: yeevonwong@unisel.edu.my.

Cathy Mae Toquero is an associate professor V of the College of Education, Mindanao State University-General Santos City, Philippines. She is an active regular member of the National Research Council of the Philippines. She integrates disability lens in pedagogy and praxis to advocate for humaneness, equality, inclusivity, and social justice toward people with disabilities. She can be contacted at email: cathymaetoquero@gmail.com.

Karen Joy B. Talidong is an assistance professor at Sultan Kudarat State University, Philippines. Her research interests include English language teaching, English as a second language, and the impact of COVID-19 on education. She can be contacted at email: karentalidong@sksu.edu.ph.