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Socio-Spatial Learning Analytics in Co-located Collaborative Learning Spaces: A Systematic Literature Review

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Abstract

Socio-spatial learning analytics (SSLA) is an emerging area within learning analytics research that seeks to uncover valuable educational insights from individuals' social and spatial data traces. These traces are captured automatically through sensing technologies in physical learning spaces, and the research is commonly based on the theoretical foundations of social constructivism and cultural anthropology. With its growing empirical basis, a systematic literature review is timely in order to provide educational researchers and practitioners with a detailed summary of the emerging works and the opportunities enabled by SSLA. This paper presents a systematic review of 25 peer-reviewed articles on SSLA published between 2011 and 2023. Descriptive, network, and thematic analyses were conducted to identify the citation networks, essential components, opportunities, and challenges enabled by SSLA. The findings illustrated that SSLA provides the opportunity to (1) contribute unobtrusive and unsupervised research methodologies, (2) support educators' classroom orchestration through visualizations, (3) support learner reflection with continuous and reliable evidence, (4) develop novel theories about social and collaborative learning, and (5) empower educational stakeholders with the quantitative data to evaluate different learning spaces. These findings could support learning analytics and educational technology scholars and practitioners to better understand and utilize SSLA to support future educational research and practice.

Notes for Practice

- Socio-spatial learning analytics (SSLA) can uncover meaningful educational insights from learners' and educators' social and spatial behaviour traces in co-located learning spaces, where the majority of the interaction and collaboration unfolds in the physical space instead of being fully mediated by computers.
- This systematic literature review identifies the prominent theoretical and empirical works, sensing technologies, learning contexts, sensing technologies, socio-spatial behaviours, and educational constructs investigated in prior SSLA studies.
- SSLA provides five opportunities for supporting educational research and practices: contributing innovative research methodologies, supporting classroom orchestration, supporting learner reflection, developing novel theories, and evaluating learning spaces.

Keywords

Socio-spatial learning analytics, collaborative learning, systematic literature review, social interaction, ubiquitous computing.

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1. Introduction

Social and spatial (socio-spatial) learning can be defined as an integrative approach that combines aspects of both social and spatial learning. It is a holistic process of learning that occurs through the interaction of individuals with each other and their surrounding environment (Bandura & Walters, 1977; Lefebvre & Nicholson-Smith, 1991; Lave & Wenger, 1991). Specifically, socio-spatial learning in co-located collaborative spaces provides an irreplaceable opportunity for students to practise and develop essential procedural and collaboration skills where they need to interact with each other (*social aspects*) and utilize different learning resources and spaces (*spatial aspects*) to achieve a shared goal (Ioannou et al., 2019). This type of learning is particularly common, for example, in high-stakes sectors such as learning emergency response and teamwork in healthcare and firefighting, where inadequate socio-spatial behaviours (e.g., task prioritization and team communication failures) could lead to severe consequences (Adrot & Bia Figueiredo, 2019; Ludlow et al., 2021). Socio-spatial learning is also important for novice teachers to learn how to make effective use of the learning space to enhance their interactions with students (spatial pedagogy (Lim et al., 2012)) and how to coordinate with other teachers in situations that involve team teaching or open learning spaces (Martinez-Maldonado, Echeverria, Schulte, et al., 2020; Yan, Martinez-Maldonado, Zhao, et al., 2022). Consequently, capturing and understanding the socio-spatial aspects of learning can provide valuable insights that can support collaborative learning and teaching practices.

Socio-spatial learning analytics (SSLA) can be defined as the emerging area of learning analytics research that aims at uncovering meaningful educational insights from learners' and educators' social and spatial behaviour traces in co-located learning spaces, where the majority of the interaction and collaboration unfold in the physical space instead of being fully mediated by computers (Martinez-Maldonado, Echeverria, Schulte, et al., 2020; Yan, Martinez-Maldonado, Gallo Cordoba, et al., 2022). While relatively few papers have directly employed the term SSLA, numerous studies have alluded to the same concept by using diverse terminology, including social, spatial, position, and location analytics (Yan, Zhao, et al., 2022). The advancements in learning analytics and sensing technologies have enabled socio-spatial data traces (e.g., the duration of co-location between two students and their interaction at spaces of interest) to be captured automatically in co-located learning spaces (Cukurova et al., 2020; Ochoa, 2022), providing unprecedented opportunities to investigate complex educational constructs (e.g., team collaboration and social dynamics) through the lens of social constructivism and cultural anthropology—the theoretical foundations of SSLA (Yan, Martinez-Maldonado, Zhao, Dix, et al., 2023).

SSLA is demonstrating its potential for supporting educational research and practice through a growing body of *in-the-wild* studies. Prior SSLA studies often involved deploying wearable position tracking systems or using advanced computer vision algorithms in physical learning spaces to identify teachers' space utilization and estimate students' social interactions from indoor positioning and proximity data (An et al., 2018; Chng et al., 2020). Specifically, SSLA, generated from individuals' spatial movements and interpersonal distances, has been used to investigate educators' spatial pedagogy (Lim et al., 2012) in science labs (Martinez-Maldonado, Schulte, et al., 2020) and open learning spaces (Yan, Martinez-Maldonado, Zhao, et al., 2022). Likewise, learners' team dynamics and task prioritization strategies in simulation-based learning have also been captured using SSLA to provoke reflection (Echeverria et al., 2018; Fernandez-Nieto, Martinez-Maldonado, Echeverria, et al., 2021). Educational stakeholders have also demonstrated a profound interest in SSLA to aid classroom orchestration and provide behavioural evidence to support reflective activities (Saquib et al., 2018; Prieto et al., 2020; Fernandez-Nieto, Martinez-Maldonado, Kitto, et al., 2021).

With the growing empirical basis of SSLA, the opportunities and challenges of this novel area of learning analytics need to be systematically summarized for the benefit of the learning analytics and educational technology communities. Although previous systematic literature reviews have indirectly included some SSLA studies (Chua et al., 2019; Yan, Zhao, et al., 2022), they have often been reviewed for purposes that concern mostly multimodal learning analytics (e.g., automated analysis and data fusion) instead of specifically focusing on the socio-spatial dimensions of learning analytics. While multimodal learning analytics and SSLA are closely related, the former focuses on using a wide variety of multimodal data (e.g., physical and physiological data (Sharma & Giannakos, 2020)) to unpack the complexity of learning across both digital and physical contexts (Crescenzi-Lanna, 2020). In comparison, SSLA focuses specifically on capturing educational insights in non-computer mediated contexts from the socio-spatial perspective, which adopts a unique set of theoretical foundations and methodologies (e.g., spatial pedagogy (Lim et al., 2012) and instructional proxemics (Chin et al., 2017)). With the rapid proliferation of the use of sensing technologies for supporting learning activities, various studies have started to look at the socio-spatial learning aspects but spread around different fields (e.g., among learning analytics (Fernandez-Nieto, Martinez-Maldonado, Kitto, et al., 2021; Zhao et al., 2023), educational technologies (Yan, Martinez-Maldonado, Zhao, Dix, et al., 2023; Yan, Martinez-Maldonado, Gallo Cordoba, et al., 2022), and human-computer interaction research (Saquib et al., 2018; Fernandez-Nieto et al., 2022)). A systematic literature review would be timely to identify the research trends and gaps in SSLA in order to provide direction to this strand of research.

This paper presents a systematic literature review of SSLA research in co-located learning spaces. The findings of this review contribute insights into the prominent theoretical and empirical works that are essential to the development of SSLA research; learning contexts, technologies, behaviours, and educational constructs that have been investigated in prior studies; the opportunities SSLA offers to support future educational research and practice; and the challenges that future SSLA studies need to address in order for SSLA innovations to benefit authentic learning practices.

2. Background and Related Work

2.1 Social Constructivism and Learning Analytics

A social constructivist perspective views education as a social process (Kim, 2010), emphasizing the essential role of interaction and collaboration among learners and educators in shaping individuals' knowledge construction and learning experience. Over the past two decades, social constructivism has contributed to the global paradigm shift from teacher-centred to student-centred learning in traditional and online learning (Baeten et al., 2010; Coleman & Money, 2020). Capturing this social process and generating analytics to support collaboration has been one of the primary focuses of learning analytics and educational technology research (Buckingham Shum & Ferguson, 2012; Chen & Teasley, 2022; Poquet & Joksimović, 2022). Prior work on social learning analytics has already demonstrated the meaningful educational insights contained within learners' social behaviours during computer-supported collaborative learning in online learning contexts, such as fostering learner engagement and predicting academic performance (Gašević et al., 2013; Chen et al., 2018; Kaliisa et al., 2022). Likewise, learning analytics tools and dashboards based on digital social traces have shown evident relevance for supporting educators to facilitate and regulate computer-supported collaborative learning (van Leeuwen et al., 2019; Chen & Teasley, 2022).

2.2 SSLA

Besides supporting computer-mediated learning contexts, learning analytics also has the potential to reveal the social aspects of educational practices in co-located settings. This potential could be realized by analyzing learners' and educators' social behaviours in the physical classroom. Although capturing social behaviour traces has been one of the major barriers to the advancement of learning analytics research in physical learning spaces due to the intrusiveness and labour-intensiveness of traditional data collection approaches (e.g., survey, interview, and direct observation) (Luciano et al., 2018; Crescenzi-Lanna, 2020), recent developments in multimodal learning analytics have demonstrated the potential of automating data collection in co-located learning spaces based on different modalities of physical or physiological behaviours captured by sensing technologies (e.g., physical proximity and physiological synchrony) (Sharma & Giannakos, 2020; Crescenzi-Lanna, 2020).

Research on SSLA endeavours to undercover meaningful educational insights from learners' and educators' socio-spatial behaviours (e.g., the duration of co-location between two students and the interaction with spaces of interest) in co-located learning spaces (Martinez-Maldonado, Echeverria, Schulte, et al., 2020; Yan, Martinez-Maldonado, Zhao, Dix, et al., 2023). These socio-spatial behaviours have proven relevant for understanding higher-order educational constructs based on the empirical findings of prior research (Lim et al., 2012; Chin et al., 2017). For example, teachers' in-class socio-spatial behaviours are associated with students' learning experiences, especially their participation in classroom activities (Chin et al., 2017) and learning motivation (Fernandes et al., 2011). Likewise, students' in-class socio-spatial behaviours have also been related to their academic success, mental well-being, and learning satisfaction (Montague & Rinaldi, 2001; Dewiyanti et al., 2007; Gašević et al., 2013).

This sub-field of research is also distinctly different from multimodal learning analytics studies (Yan, Zhao, et al., 2022), which are predominantly based on cognitive (e.g., the embodiment theory (Shapiro & Stolz, 2019)) and emotional (e.g., the control value theory of achievement emotion (Pekrun, 2006)) theories. Spatial features (e.g., proximity and body orientation) are theoretically grounded by specific theories of social constructivism and cultural anthropology. Specifically, Hall's (1966) foundational theory on proxemics entails the association between the proximity individuals maintained with each other during social encounters and the nature of their social relationships, providing the theoretical basis for analyzing individuals' socio-spatial behaviours from their positioning and movement in physical learning spaces. The empirical basis for socio-spatial analysis could also be found in prior social psychology studies, which have illustrated the high predictivity of physical proximity in estimating interpersonal relationships among friends and acquaintances (Back et al., 2008).

Over the past few years, a growing body of research on SSLA has been published, spanning leading learning analytics (Fernandez-Nieto, Martinez-Maldonado, Kitto, et al., 2021; Zhao et al., 2023), AI in education (Chng et al., 2020; Martinez-Maldonado, Echeverria, Schulte, et al., 2020), educational technology (Yan, Martinez-Maldonado, Zhao, Dix, et al., 2023; Yan, Martinez-Maldonado, Gallo Cordoba, et al., 2022), and human-computer interaction (Saquib et al., 2018; Fernandez-Nieto et al., 2022) venues. Existing research has illustrated the potential of SSLA for investigating different educational constructs (e.g., team collaboration (An et al., 2018) and spatial pedagogy (Yan, Martinez-Maldonado, Zhao, et al., 2022)) in a wide range of learning contexts (e.g., early education (Saquib et al., 2018) and clinical simulations (Fernandez-Nieto, Martinez-Maldonado, Kitto, et al., 2021)). Some of these studies have been indirectly included in previous systematic literature reviews on multimodal learning analytics (Sharma & Giannakos, 2020; Crescenzi-Lanna, 2020; Yan, Zhao, et al., 2022).

However, these prior studies have spanned multiple research fields (beyond multimodal learning analytics) and have yet to be systematically reviewed for their own merit. Consequently, the opportunities enabled by this novel area of research could remain unknown to learning analytics and educational technology scholars and practitioners. Likewise, the challenges that future SSLA studies need to address for this area of learning analytics to achieve its full potential also remain unclear. For example, understanding the technological readiness (Defence Science and Technology Group, n.d.) and transparency (Chaudhry et al., 2022) of SSLA solutions is critical for ensuring the responsible and ethical use of these novel technologies in authentic educational contexts.

2.3 Research Questions

The current study aims to address the existing literature gap by systematically reviewing the publications on SSLA in co-located learning contexts. The overarching goal of this systematic literature review is to provide a detailed summary of the existing SSLA research and pinpoint the prominent theoretical and empirical works that are influential to the development of this novel research area. Drawing on the research questions in previous systematic literature reviews on an emerging area of learning analytics (Poquet et al., 2018; Bodily et al., 2018), the following research questions were investigated to guide the current review:

- **RQ1:** What prominent theoretical and empirical works supported the development of SSLA research?
- **RQ2:** What learning contexts, sensing technologies, socio-spatial behaviours, and educational constructs are studied in SSLA research?
- **RQ3:** What opportunities does SSLA offer to support educational research and practice?
- **RQ4:** What challenges do future SSLA studies need to address?

2.4 Contribution to Learning Analytics Research

The systematic literature review presented in this paper goes beyond prior learning analytics reviews by focusing specifically on SSLA in co-located learning spaces. To the best of our knowledge, this study is the first review to systematically summarize the opportunities and challenges enabled by SSLA. The contribution of this study to the learning analytics community is threefold: (1) we present the first systematic literature review on a novel area of learning analytics research—SSLA, (2) we identify the prominent theoretical and empirical works that are influential to the development of SSLA, and (3) we summarize the opportunities and challenges of SSLA for supporting future educational research and practice.

3. Methods

3.1 PRISMA Protocol for Systematic Literature Review

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (Page et al., 2021) protocol was used to guide the current systematic literature review. This four-phase protocol ensures the transparent reporting of systematic reviews. Specifically, the phases include identifying eligible studies from multiple databases, screening the title and abstract of the identified studies, reviewing the full texts of the screened studies, and extracting data from the included studies. Four renowned bibliographic databases were searched to retrieve high-quality peer-reviewed publications on SSLA: Scopus, ACM Digital Library, IEEE Xplore, and Web of Science. The following search query was used to search through the title, abstract, and keywords of peer-reviewed publications: ("social" OR "spatial") AND ("proximity" OR "proxemics" OR "position" OR "location") AND ("classroom" OR "school" OR "face-to-face" OR "face to face" OR "co-locate*" OR "collocate*" OR "physical learning space*") AND ("learning analytics" OR "classroom analytics" OR "insights" OR "feedback"). A publication year constraint was also applied to limit the search to studies published between 2011 and March 13, 2023, because learning analytics was formally established as a research field after 2010 with the launch of the LAK conference in 2011 (Blikstein, 2013). The initial database search returned 1,932 publications with 355 duplicates removed, resulting in 1,577 publications for the title and abstract screen (Figure 1).

Two researchers independently reviewed the titles and abstracts for eligible articles based on five inclusion and exclusion criteria. First, we included studies conducted in co-located learning contexts where most learners' and educators' social and spatial behaviours unfolded in the physical world. Studies that merely focused on computer-mediated learning contexts, such as MOOCs and LMS, were excluded from this review. While it is also possible to co-locate virtually as an avatar in a virtual reality environment, where SSLA may also apply, the current study focused primarily on co-location in physical learning spaces.

Second, empirical studies that have provided detailed information regarding their methodology and results were included, with the exclusion of literature reviews, scoping studies, and conceptual works. Third, studies that used SSLA to inform on high-order educational constructs (e.g., task prioritization and collaboration) were included, excluding studies that only focused on modelling socio-spatial behaviours because these studies often lack educational implications. Additionally, we included studies that used sensing technologies to automate the capture of socio-spatial behaviour traces and excluded studies that only used surveys, interviews, or human observations. Lastly, we only included full-length research articles in conference proceedings and journals, excluding short papers, extended abstracts, keynotes, posters, workshop proceedings, and book chapters (Page et al., 2021). The conflicting decisions were resolved through further discussion or consulting a third researcher for consensus.

As shown in Figure 1, 60 publications were eligible for the full-text review. The inter-rater reliability, measured as Cohen's kappa, was 0.80, indicating a substantial agreement between the two researchers (McHugh, 2012). The full text of all 60 publications was successfully retrieved. A total of 25 publications were then selected for data extraction with an inter-rater reliability of 0.96 (Cohen's kappa), indicating almost perfect agreement between the two researchers during the full-text review (McHugh, 2012). The inter-rater reliability values were calculated before the conflict resolution process, following the PRISMA protocol (Page et al., 2021). The 35 publications were excluded for six different reasons: 12 publications lacked socio-spatial data, eight publications lacked educational constructs (e.g., studies that mentioned some educational constructs as implications instead of as part of the body of the study), seven publications were not full-length papers, five publications lacked sensing technologies, two publications were conducted in computer-mediated contexts, and one publication was not an empirical study. The following subsections elaborate on the data extraction and analysis conducted to answer each research question.

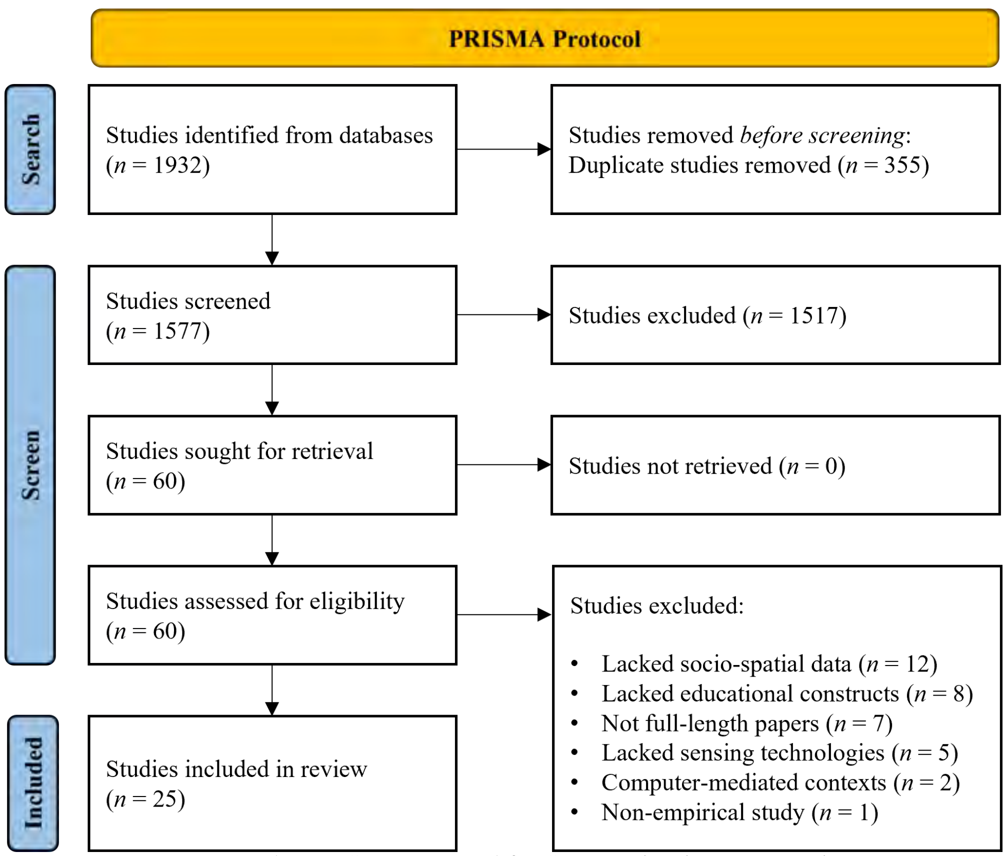

Figure 1. The PRISMA Protocol for Systematic Literature Review

3.2 Citation Network Analysis (RQ1)

A citation network analysis was conducted to identify the prominent theoretical and empirical works that supported the development of SSLA research (RQ1) among the 1,475 citations from the 25 included studies. Citation network analysis is a type of social network analysis that assesses the relationships between reviewed publications and their citations. We adopted the methodology presented by Dawson and colleagues (2014) but focused primarily on the publication citation network instead of the author citation network, since our goal was to identify prior theoretical and empirical works that had influenced

SSLA research. A directed social network was created among the reviewed and cited publications. Specifically, if a reviewed publication, P1, cited three other papers, C1, C2, and C3, then four nodes were created, and directed edges were drawn between P1 and C1, P1 and C2, and P1 and C1 to establish the publication citation network. Each publication could only have one edge (unweighted) with a specific citation regardless of the number of times it had been cited (Dawson et al., 2014). The influence of a publication on SSLA research was measured by its in-degree (Das et al., 2018), that is, the number of times a given publication had been cited in SSLA research. The Google Scholar citation of the top 10 prominent theoretical and empirical works was also collected to assess the influences of these works on the broader academic community. We also compared the top 10 most cited SSLA publications with prominent theoretical and empirical works to identify potential overlaps, which may indicate the overall connectedness of SSLA research.

3.3 Thematic Analysis (RQ2–4)

To address the remaining three research questions, we first extracted data regarding learning contexts, sensing technologies, socio-spatial behaviours, and educational constructs (RQ2). An inductive thematic analysis was conducted to address RQ3 by organizing and grounding similar terminologies into one category. For example, in terms of educational constructs, publications that studied learners' academic progression (Yan et al., 2021) were grouped with publications that studied learners' task performance (Chng et al., 2020) under the label "academic performance." We followed the reflexive thematic analysis approach, which involves letting the themes for each category emerge by themselves, instead of using a pre-defined codebook (Braun & Clarke, 2019). A Sankey diagram was constructed to illustrate the relationship and "flow" between these different components of SSLA. Sankey diagrams are a type of flow diagram in which the width of the vertical bars represents the quantity and proportion of the items in each component, and the width of the arrows represents the quantity of the "flow" between different categories. For example, the "flow" from simulation-based learning to wearable trackers in Figure 2 indicates the quantity and proportion of the included studies conducted in simulation-based learning settings that have adopted wearable trackers to capture socio-spatial behavioural traces.

Thematic content analyses were conducted to extract the main themes discussed in the reviewed publications regarding the opportunities (RQ3) of SSLA for supporting future educational research and practice. These analyses were done by first extracting the opportunities mentioned in each publication. These extracted opportunities were then coded based on the emerging themes. For example, a publication that mentioned its opportunity to support students' reflective practice in post-simulation debrief (Fernandez-Nieto, Martinez-Maldonado, Kitto, et al., 2021) was coded as "supporting learning reflection." We then categorized the codes by grouping codes with similar meanings into an overarching theme, such as supporting educators' decision-making process (Martinez-Maldonado, Mangaroska, et al., 2020; An et al., 2018) and unfolding classroom social dynamics (Saquib et al., 2018; Yan et al., 2021). Finally, the ethical and privacy challenges of SSLA, as a part of RQ4, were also summarized through content analyses.

3.4 Additional Analysis (RQ4)

For the final research question (RQ4), we also assessed the technological readiness of the existing SSLA studies using the Australian Department of Defence's Technology Readiness Levels (TRLs) (Defence Science and Technology Group, n.d.). TRLs have been used in previous systematic literature reviews to pinpoint potential practical challenges that may arise from the immaturity of a research area (Yan, Zhao, et al., 2022). For example, SSLA innovations with a low TRL, either in TRL-1 (Basic Research), TRL-2 (Applied Research), or TRL-3 (Critical Function or Proof of Concept Established), may face usability and functionality issues because such innovations have yet to be tested and validated by users. SSLA innovations with a medium TRL, including TRL-4 (Lab Testing/Validation of Alpha Prototype Component/Process), TRL-5 (Laboratory Testing of Integrated/Semi-Integrated System), and TRL-6 (Prototype System Verified), may encounter acceptance and adoption issues because these innovations have only been verified under laboratory and controlled settings, with little evidence on how stakeholders will use them in authentic learning contexts. On the other hand, scalability and sustainability issues might be the barriers to wide adoption for SSLA innovations with a high TRL, including TRL-7 (Integrated Pilot System Demonstrated), TRL-8 (System Incorporated in Commercial Design), and TRL-9 (System Proven and Ready for Full Commercial Deployment). We further elaborate on the details of these TRLs in Section 4.4.

Assessing the transparency of SSLA studies could provide additional insights regarding potential practical challenges. The transparency index (Chaudhry et al., 2022) was used to assess the transparency of the technological innovations developed in SSLA studies. The original transparency index contained three tiers: Tier 1—transparent to AI researchers and practitioners, Tier 2—transparent to educational technology experts and enthusiasts, and Tier 3—transparent to educators and parents. Although this framework was originally developed to assess the transparency of AI systems, it can also be applied to SSLA innovations because they have many similarities. For example, they both aim to automate some aspects of the educational process and generate meaningful insights for stakeholders. However, in the context of SSLA, Tier 1 transparency could involve providing sufficient details about the sensing technologies and the machine learning algorithms for generating SSLA, which can be considered transparent to multimodal learning analytics researchers and practitioners. Tier 2 can be considered transparent to general learning analytics experts and enthusiasts. For Tier 3, we also included students as one of the important stakeholders because SSLA may directly influence students' reflective practices (Zhao et al., 2023; Yan, Martinez-Maldonado, Zhao, Dix, et al., 2023).

Two reviewers independently coded the TRL and transparency index of each included study. The inter-rater reliability values, Cohen's kappa (calculated before conflict resolution), were 0.68 and 0.76, respectively, indicating substantial agreement between the two reviewers. The conflicts were resolved through further discussion or by consulting a third researcher for consensus.

4. Results

4.1 RQ1—Citation Network

Other than the most cited publication (Stehlé et al., 2013), nine of the top 10 most cited publications introduce a novel approach to extracting SSLA from learners' and educators' behavioural traces in physical learning spaces (Table 1). For example, EduSense (Ahuja et al., 2019), ClassBeacons (An et al., 2018), Sensei (Saquib et al., 2018), and Moodoo (Martinez-Maldonado, Echeverria, Schulte, et al., 2020) are all named approaches for modelling SSLA using sensing technologies. This finding was expected because SSLA is in its infancy. Developing novel analytic approaches and methodologies is essential for analyzing socio-spatial trace data and generating educational insights.

Table 1. The Top 10 Most Cited SSLA Publications Based on Google Scholar Citations as of March 2023

Publication Title	Citations
Gender homophily from spatial behavior in a primary school: A sociometric study (Stehlé et al., 2013)	110
EduSense: Practical classroom sensing at Scale (Ahuja et al., 2019)	90
From data to insights: A layered storytelling approach for multimodal learning analytics (Martinez-Maldonado, Echeverria, Fernandez Nieto, et al., 2020)	54
Where is the nurse? Towards automatically visualising meaningful team movement in healthcare education (Echeverria et al., 2018)	48
Sensei: Sensing educational interaction (Saquib et al., 2018)	34
ClassBeacons: Designing distributed visualization of teachers' physical proximity in the classroom (An et al., 2018)	33
Quantifying classroom instructor dynamics with computer vision (Bosch et al., 2018)	27
Moodoo: Indoor positioning analytics for characterising classroom teaching (Martinez-Maldonado, Echeverria, Schulte, et al., 2020)	26
Teacher tracking with integrity: What indoor positioning can reveal about instructional proxemics (Martinez-Maldonado, Mangaroska, et al., 2020)	25
Where is the teacher? Digital analytics for classroom proxemics (Martinez-Maldonado, Schulte, et al., 2020)	18

As shown in Table 2, five of the top 10 most prominent theoretical and empirical works (highest in-degree) were also listed in the top 10 most cited SSLA publications (Table 1) (Saquib et al., 2018; Ahuja et al., 2019; Martinez-Maldonado, Schulte, et al., 2020; Martinez-Maldonado, Mangaroska, et al., 2020; Martinez-Maldonado, Echeverria, Schulte, et al., 2020). This finding could indicate that the SSLA research community is well connected, where researchers are familiar with others' empirical work and acknowledge their contributions. Of the other five citations, the most influential theoretical work was Hall's groundbreaking work on the theory of proxemics (cited by nine reviewed publications) (Hall, 1966). Surprisingly, this foundational piece was not the most cited in the reviewed publications. A closer look at the in-degree of the citations revealed that many reviewed publications also cited Hall's other papers. For example, one of his later works on proxemics (Hall et al., 1968) was cited by five publications. Additionally, one of the important citations (Sorokowska et al., 2017) focused exclusively on providing empirical evidence regarding proxemics and interpersonal distance across different cultures. After considering these factors, Edward T. Hall's work on proxemics remains the most prominent theoretical work that has provided the theoretical foundations for advancing SSLA research. Other than this influential work, we also identified two prominent works that are either a conceptual (Martinez-Maldonado et al., 2018) or a review (Chua et al., 2019) work, indicating the perceived need for authors to define and explain their work based on other related areas of learning analytics (e.g., from multimodal and physical learning analytics), which is expected in an emerging research area (Dawson et al., 2014).

Table 2. The Top 10 Most Prominent Citations with the Highest In-degree and Their Google Scholar Citation

Citation Title	In-degree	Citations
1 Sensei: Sensing educational interaction (Saquib et al., 2018)	14	34
2 *The hidden dimension* (Hall, 1966)	11	17,488
3 Where is the nurse? Towards automatically visualising meaningful team movement in healthcare education (Martinez-Maldonado, Schulte, et al., 2020)	11	48
4 Moodoo: Indoor positioning analytics for characterising classroom teaching (Martinez-Maldonado, Echeverria, Schulte, et al., 2020)	10	26
5 EduSense: Practical classroom sensing at Scale (Ahuja et al., 2019)	10	90
6 Physical learning analytics: A multimodal perspective (Martinez-Maldonado et al., 2018)	9	58
7 Footprints at school: Modelling in-class social dynamics from students' physical positioning traces (Yan et al., 2021)	9	16
8 Technologies for automated analysis of co-located, real-life, physical learning spaces: Where are we now? (Chua et al., 2019)	8	32
9 Teacher tracking with integrity: What indoor positioning can reveal about instructional proxemics (Martinez-Maldonado, Mangaroska, et al., 2020)	8	25
10 Towards collaboration translucence: Giving meaning to multimodal group data (Echeverria et al., 2019)	8	75

4.2 RQ2—Contexts, Technology, Behaviours, and Constructs

4.2.1 Learning Contexts

As shown in the Sankey diagram (Figure 2), we identified six learning contexts where SSLA research was conducted. Simulation-based learning is one of the most prevalent learning contexts observed in eight prior SSLA studies. These studies were conducted in clinical simulations where a team of four students worked on one (Echeverria et al., 2018; Fernandez-Nieto, Martinez-Maldonado, Echeverria, et al., 2021) or multiple (Zhao et al., 2022; Yan, Martinez-Maldonado, Zhao, Dix, et al., 2023) patient beds in immersive physical simulation classrooms. Collaborative learning contexts were also investigated by eight prior studies but covered a wide range of learning spaces, including an early education centre (Saquib et al., 2018), collaborative classrooms (Martinez-Maldonado, Mangaroska, et al., 2020), secondary school classrooms (An et al., 2018), open learning spaces (Yan et al., 2021; Yan, Martinez-Maldonado, Gallo Cordoba, et al., 2022; Yan, Martinez-Maldonado, Zhao, et al., 2022), a school library (Riquelme et al., 2020), and an immersive exhibition centre (Mallavarapu et al., 2022). Five studies were conducted in laboratory learning contexts, such as digital fabrication labs (Chng et al., 2020) and physics labs (Martinez-Maldonado, Echeverria, Schulte, et al., 2020; Martinez-Maldonado, Mangaroska, et al., 2020; Martinez-Maldonado, Schulte, et al., 2020; Fernandez-Nieto et al., 2022). Two studies were conducted in lecture-based learning contexts, such as lecture classrooms with fixed seating (Bosch et al., 2018; Ahuja et al., 2019). Finally, one study was conducted in a primary school playground and canteen (Stehlé et al., 2013), and another was conducted on the scale of a university campus (Nguyen et al., 2020).

4.2.2 Sensing Technologies

We identified four types of sensing technologies in prior studies to capture socio-spatial behaviours (Figure 2). Wearable trackers were the most predominant sensing technology, used in 16 prior studies. This type of technology often requires physically installing positioning locators or anchors on the learning spaces' walls or ceilings and distributing a wearable tracker that transmits positioning signals to each learner and educator (Martinez-Maldonado, Echeverria, Schulte, et al., 2020; Yan, Martinez-Maldonado, Zhao, Li, et al., 2023). Such systems are often quite expensive to deploy. For example, Yan, Martinez-Maldonado, Zhao, and colleagues (2022) installed an enterprise-level indoor positioning tracking system in an open-plan primary school building (over 400 square metres), which involved installing 14 Quuppa LD6-L locators (US$1,200 each) on the ceilings and distributing six Jeewey JW-C1809C card tags (US$20 each) and 98 Tatwah Mango BLE-WB200 wristbands (US$20 each) to teachers and students, respectively, for receiving and transmitting positioning data via Bluetooth using the angle of arrival method (Quuppa, 2023). The total equipment cost of such a comprehensive system is around US$17,038, with additional installation and technician-related expenses (e.g., electrical wiring and system configuration). Such expensive systems might be impractical to implement at a large scale and might only be suitable for research purposes unless the cost goes down substantially (Yan, Zhao, et al., 2022). Smaller systems have also been deployed in laboratories

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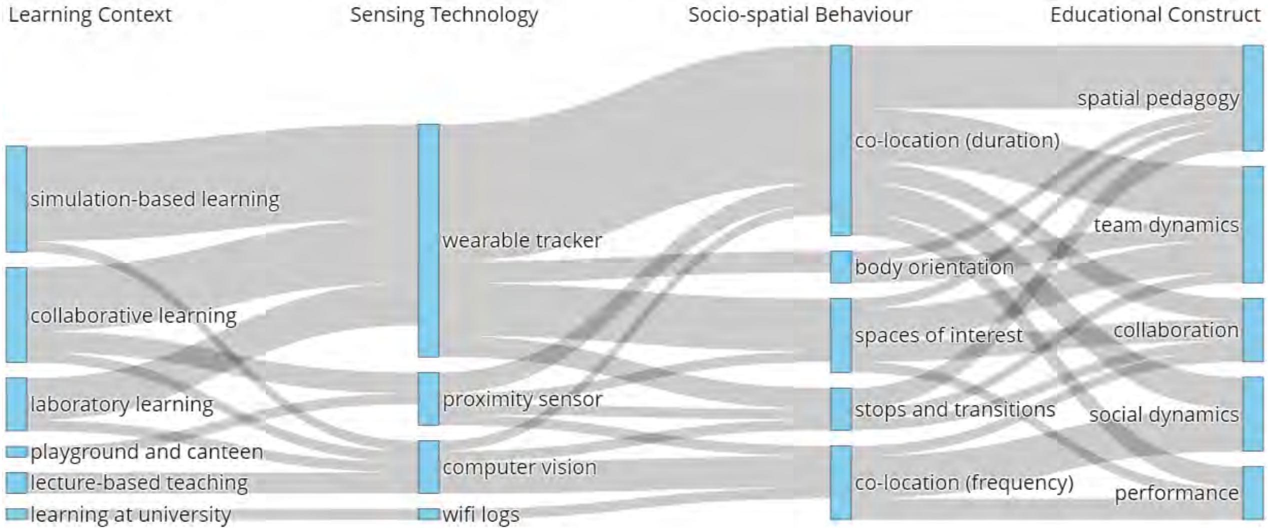

Figure 2. Sankey Diagram Showing the Flow between Different Components of SSLA

(Martinez-Maldonado, Mangaroska, et al., 2020) and clinical simulation classrooms (Zhao et al., 2023), which involved the Pozyx (Pozyx, 2023) creator kit (approximately US$1,200) with four ultra-wideband location anchors and six positioning tracking tags. The utility of such smaller systems could potentially outweigh their financial cost when used in specialized classrooms for multiple groups of students/teachers (e.g., 208 students participating in clinical simulations in groups of four for each session (Yan, Martinez-Maldonado, Zhao, Dix, et al., 2023)).

The proximity sensors used in three studies, however, do not require additional physical installation. Instead, putting these sensors in different areas of learning spaces is sufficient to capture whether individuals were located within a given area (e.g., within one metre of the students' table (An et al., 2018)). The unit price of these devices (e.g., the Estimote development kit is around US$99 (Estimote, 2023)) is also much less than wearable trackers because they do not require any additional anchors or locators to triangulate the precise coordinates. However, individuals need to have a device on them that is connected to the Internet or a mesh network (Saquib et al., 2018) (e.g., a cellphone or a proximity sensor) to receive the signals from other proximity sensors in order to transmit the proximity data for processing (Riquelme et al., 2020). Additionally, the practical implication of these proximity sensors could also be limited because they do not record any coordinate data and thus are unable to provide insights into individuals' transition behaviours and movement trajectory, which are vital information for modelling teachers' spatial pedagogy (Yan, Martinez-Maldonado, Zhao, et al., 2022).

Five prior studies used computer vision techniques to capture socio-spatial behaviours from video recordings. While these techniques require much fewer material resources than wearable trackers and proximity sensors (e.g., any cameras are sufficient (Mallavarapu et al., 2022)), they are less automated because human resources are required to clean and label data for the computer vision algorithms to achieve optimum accuracy (Chng et al., 2020; Ahuja et al., 2019). Li and colleagues (2023) presented the first automated computer vision techniques to capture socio-spatial behaviours from video recordings in educational settings. The proposed approach tracks individual position and movement with an object tracking algorithm (MMTracking (Bewley et al., 2016)) while preserving individuals' privacy with masked facial identity. Although this method is currently not as reliable as indoor positioning systems with wearable trackers, especially for socio-spatial behaviours that unfold in close proximity, the authors suggested that future versions that use videos' depth information could potentially improve its reliability, making it a plausible alternative to the expensive tracker-based systems.

One prior study (Nguyen et al., 2020) has used WiFi logs to determine whether learners are in the same building based on the WiFi access point connected to by their personal electronic devices, which requires no additional material or human resources but is subject to many technical issues (e.g., disconnection and network interference) and questionable accuracy (e.g., learners connected to the WiFi in one building but physically located in a different space).

4.2.3 Socio-Spatial Behaviours

Five different types of socio-spatial behaviours were identified in prior studies. Specifically, co-location (frequency) and co-location (duration) refer to the frequency or the duration that two individuals have been identified as being close to each other based on a certain proximity threshold (e.g., within one-metre Euclidean distance (Martinez-Maldonado, Echeverria, Schulte, et al., 2020)). Spaces of interest are particular areas of learning spaces that have been infused with certain meanings based on the learning designs or stakeholders' inputs. For example, a clinical simulation classroom can be further divided into several primary and secondary task spaces based on the learning tasks related to each space according to teachers' learning designs (Yan, Martinez-Maldonado, Zhao, Dix, et al., 2023). Stops and transitions are spatial behaviours that contain insights into whether individuals have remained stationary at a given location or are moving from one location to another. Body orientation refers to an individual's front-facing direction. As shown in Figure 3, these behaviours exhibit various granularity, that is, the level of meaningful detail contained within these behaviours and the additional information required to identify such behaviours. For example, co-location (frequency), captured in five prior studies ($n = 5$), has the lowest granularity because only information regarding whether two individuals are in close proximity is required, which can be captured by proximity sensors that register instances of co-location based on certain thresholds (Stehlé et al., 2013; Nguyen et al., 2020). Individuals' interactions at spaces of interest ($n = 8$) exhibit a higher granularity than co-location (frequency) because these behavioural features require knowing the coordinates of people in the physical space and additional contextual information to give meaning to the specific locations (Riquelme et al., 2020). Co-location (duration), captured in 16 prior studies, requires continuous data to model exactly how long two people have remained close to each other (An et al., 2018), which is not necessarily required for the prior two behaviours. Identifying stops and transitions ($n = 5$) would require further precision (e.g., at sub-metre level) in continuous tracking of teachers or students to identify walking trajectories in the learning space (Martinez-Maldonado, Echeverria, Schulte, et al., 2020). Body orientation ($n = 3$) relative to the configuration of the learning space exhibits the highest granularity among these five behaviours, because it requires an additional three-dimensional reference system to know where a person is facing. This behavioural feature has shown benefits in supporting educational stakeholders to comprehend socio-spatial visualizations (e.g., heatmaps), especially when an individual is near multiple objects or persons of interest (e.g., whether a teacher is facing the whiteboard or students) (Fernandez-Nieto et al., 2022).

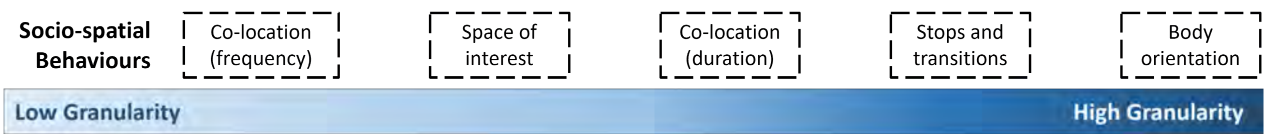

Figure 3. The Granularity of the Socio-Spatial Behaviours

4.2.4 Educational Constructs

Prior studies have generated SSLA on six different educational constructs. Six studies ($n = 7$) have investigated educators' spatial pedagogy using SSLA. For example, teachers' spatial distribution among multiple student groups was reflected through ClassBeacons, an ambient information system that indicates the time a teacher is near different student groups (An et al., 2018). Teachers' spatial pedagogical approaches characterized based on their socio-spatial behaviours were also compared across three different learning designs (Martinez-Maldonado, Echeverria, Schulte, et al., 2020) and among different school subjects (Yan, Martinez-Maldonado, Zhao, et al., 2022) to generate insights into their classroom practice (Martinez-Maldonado, Schulte, et al., 2020). These insights have shown evident relevance for understanding the association among spatial pedagogy, student cohesion, and learning designs (Yan, Martinez-Maldonado, Zhao, et al., 2022; Martinez-Maldonado, Echeverria, Schulte, et al., 2020), as well as providing actionable feedback to teachers during classroom teaching (An et al., 2018). Likewise, students' social interactions were reflected through SSLA ($n = 7$), such as the homophilic interactions among students based on gender and academic performance (Stehlé et al., 2013; Nguyen et al., 2020; Yan et al., 2021; Yan, Martinez-Maldonado, Zhao, Li, et al., 2023) and the social and ego network of individual students (Saquib et al., 2018; Yan et al., 2021). These insights regarding students' social dynamics have been used to generate diagnostic analytics for exploring the relationships among social behaviours and learning constructs (Stehlé et al., 2013; Nguyen et al., 2020) and motivate the development of descriptive (Saquib et al., 2018) and predictive analytics models (Yan, Martinez-Maldonado, Gallo Cordoba, et al., 2022) (further elaborated on in Section 4.3). SSLA was also used to inform on team dynamics ($n = 7$) in clinical simulations, such as the positioning strategies (Echeverria et al., 2018; Fernandez-Nieto, Martinez-Maldonado, Echeverria, et al., 2021), non-verbal communication (Zhao et al., 2022), verbal communication (Zhao et al., 2023), and task-related actions (Martinez-Maldonado, Echeverria, Fernandez Nieto, et al., 2020; Yan, Martinez-Maldonado, Zhao, Dix, et al., 2023; Li et al., 2023) that a team adopted when taking care of deteriorating patients. These team-related insights have shown practical value in supporting teachers to guide post hoc reflective practices (Yan, Martinez-Maldonado, Zhao, Dix, et al., 2023; Fernandez-Nieto, Martinez-Maldonado, Echeverria, et al., 2021). Additionally, SSLA was used to study academic performances ($n = 4$), in particular, for predicting students' academic progression in math and reading (Yan, Martinez-Maldonado, Gallo Cordoba, et al., 2022) and the task-related performances of individual students (Chng et al., 2020) and student groups (Yan, Martinez-Maldonado, Zhao, Dix, et al., 2023). Lastly, student collaboration was reflected by SSLA in three prior studies, specifically, for differentiating student roles (Riquelme et al., 2020), generating collaboration temperature readings (Mallavarapu et al., 2022), and reflecting students' task prioritization strategies (Yan, Martinez-Maldonado, Zhao, Dix, et al., 2023).

4.3 RQ3—Opportunities to Support Educational Research and Practice

The thematic content analysis revealed five core themes regarding SSLA's opportunities to support future educational research and practice. These opportunities include contributing research methodologies ($n = 13$), supporting classroom orchestration ($n = 9$), supporting learner reflection ($n = 7$), developing novel theories ($n = 5$), and evaluating learning spaces ($n = 3$). The following subsections elaborate on each theme.

4.3.1 Contributing Research Methodologies

One of the core themes that emerged in our analysis is the innovative research methodologies contributed by studies on SSLA. The combination of sensing technologies and SSLA could potentially overcome the shortcomings of traditional research methodologies (e.g., survey, interview, and direct observation), which are intrusive and labour intensive and rely primarily on individuals' ability to recall their memories and experiences (Luciano et al., 2018; Crescenzi-Lanna, 2020). SSLA studies have contributed unobtrusive and unsupervised methods to capture dynamical and longitudinal socio-spatial data on human behaviours at large scales (Stehlé et al., 2013; Mallavarapu et al., 2022). For example, longitudinally capturing and analyzing the social dynamics of 98 students in large open learning spaces over eight school weeks would be almost impossible without SSLA (Yan et al., 2021). Likewise, SSLA also enabled the recording and investigating of individual and group behaviours during learning activities with high temporal and spatial resolutions (Riquelme et al., 2020; Echeverria et al., 2018), providing more research opportunities to explore complex educational concepts, such as understanding the association between homophilic interaction, group cohesion, and academic performance (Wyman & Watson, 2020).

4.3.2 Supporting Classroom Orchestration

Another core theme regarding the opportunities of SSLA is the potential of supporting educators to reflect and adapt their classroom orchestration strategies. SSLA studies have contributed empirical evidence and meaningful insights into the learning and teaching process across various learning contexts (see Section 4.2.1). These insights and evidence could be operationalized using visualizations and dashboards (Martinez-Maldonado, Mangaroska, et al., 2020; Saquib et al., 2018) to support educators in making informed decisions, such as determining when to intervene during collaborative learning (An et al., 2018) and which students are at risk of falling behind academically (Yan, Martinez-Maldonado, Gallo Cordoba, et al., 2022) or are becoming increasingly socially disengaged (Saquib et al., 2018; Yan et al., 2021). Additionally, SSLA can provoke meaningful discussion on instructional design and spatial pedagogy, individually or among a collaborative teaching team (An et al., 2018; Martinez-Maldonado, Echeverria, Schulte, et al., 2020). These opportunities could benefit educators' professional development, especially for beginner or inexperienced educators adapting to complex learning spaces (Yan, Martinez-Maldonado, Zhao, et al., 2022).

4.3.3 Supporting Learner Reflection

The third core theme that emerged from the thematic content analysis involves the potential of SSLA to support learners' reflective practice. SSLA provides the opportunity to capture continuous and potentially more reliable evidence that is less susceptible to cognitive bias (Saquib et al., 2018). This evidence could be beneficial to learners for provoking reflection on their experience during complex learning activities (e.g., clinical simulations), where they could be overwhelmed by the multiple tasks they have to conduct and by the need to collaborate with others (Echeverria et al., 2018; Fernandez-Nieto, Martinez-Maldonado, Echeverria, et al., 2021). Such opportunities have been endorsed by educators who would like to use this evidence to guide and motivate learner reflection in post-simulation debriefs (Fernandez-Nieto, Martinez-Maldonado, Kitto, et al., 2021; Yan, Martinez-Maldonado, Zhao, Dix, et al., 2023).

4.3.4 Developing Novel Theories

SSLA also enables opportunities to support the development of novel educational theories. The continuous and reliable data captured in SSLA research could provide the empirical basis for understanding the complex relationships between different educational constructs (Saquib et al., 2018). For example, the temporal changes in homophilic interaction regarding learner demographics and academic performance can be made clear using SSLA, providing unprecedented opportunities to establish novel theories and models around social and collaborative learning (Stehlé et al., 2013). Likewise, new proxemics theories can also be developed using the insights generated from SSLA studies on the ecological perspectives of the learning spaces (Martinez-Maldonado, Schulte, et al., 2020), such as how the meaning of proximity and interpersonal distances changes as learners become more familiar with each other in a learning space (Yan et al., 2021).

4.3.5 Evaluating Learning Spaces

The final core theme is the potential of SSLA to open up opportunities to evaluate the effectiveness of novel architectural designs in achieving their desired educational purposes. For example, although open learning spaces and flexible classrooms promote collaboration and autonomy, how educators and learners adapt to these novel spaces would require further investigation

(Alterator & Deed, 2013). Previous attempts to explore such problems often relied on qualitative analysis, which might not reflect the whole picture of the events that unfold in the learning spaces, especially in large spaces and complex social dynamics (Whyte, 2017). The fine-grained data and evidence captured by SSLA on each learner and educator could complement and cross-validate the insights generated from focus groups and interviews, empowering educational stakeholders (e.g., school management) with detailed evidence to make informed decisions on the usage of different learning spaces and the suitability of architectural innovations (Martinez-Maldonado, Schulte, et al., 2020; Yan et al., 2021).

4.4 RQ4—Challenges for Future SSLA Studies

Assessing technological readiness and system transparency has revealed some important practical issues for future SSLA studies to address. Likewise, several ethical and privacy issues have been identified in prior literature. Investigating and addressing these challenges is essential for SSLA to achieve its full potential, fulfill the aforementioned opportunities, and have actual benefits on future learning analytics research and practices.

4.4.1 Practical Challenges

A total of 16 studies have reached at most TRL-3, which generated educational insights by applying SSLA to prior collected data. However, these insights have yet to be shown or validated by stakeholders. Consequently, these studies can only be considered transparent to multimodal learning analytics researchers and practitioners (Tier 1; $n = 12$) or learning analytics experts and enthusiasts (Tier 2; $n = 4$). The lack of stakeholder evaluation could dampen the meaningfulness and usefulness of these insights because they might be too complicated for stakeholders to comprehend. One of the prior studies has flagged this issue, where educators expressed their concerns over using epistemic networks as visual evidence for supporting student reflection (Fernandez-Nieto, Martinez-Maldonado, Kitto, et al., 2021). Eight studies have had their SSLA innovations evaluated by stakeholders in a post hoc manner, where they interviewed students or teachers and asked them to interpret visualizations and analytics generated based on prior collected data. Such involvements have enhanced educational stakeholders' understanding of the insights, thus making SSLA more transparent to them (partly Tier 3). However, the generation process of these insights can only be considered transparent to educational stakeholders in two studies (Tier 3), where they were also involved in the co-design process and actively contributed to the development of the features and metrics used in the analysis (Fernandez-Nieto, Martinez-Maldonado, Echeverria, et al., 2021; Yan, Martinez-Maldonado, Zhao, Dix, et al., 2023). Although these studies have taken the further steps of co-designing and evaluating with educational stakeholders, they have yet to provide visualizations and analytics to stakeholders as a part of the educational practices for supporting teaching and learning activities. Therefore, stakeholders' willingness to adopt these innovations remains unclear, especially for those not part of the research, because they have no prior commitment to the innovations (e.g., co-designing). Additionally, some valuable feedback that can only be obtained after stakeholders have used the innovations in practice still needs to be discovered because of this lack of field deployment. This issue is reflected in the only study that integrated a classroom orchestration tool (TRL-7; Classbeacons (An et al., 2018)) to support teachers' attention distribution management. After using the tool, one of the teachers reported that it distracted a student who is sensitive to distraction in general.

4.4.2 Ethical and Privacy Challenges

Researchers and practitioners should be aware of the ethical and privacy issues related to SSLA. These issues could involve the risk of unintended and harmful surveillance, where individuals' data can be misused or over-interpreted for performance-related assessments (Fernandez-Nieto et al., 2022; Alwahaby et al., 2022). Although privacy preservation methods, such as the use of de-identified data for group-level insights (Yan, Martinez-Maldonado, Zhao, Dix, et al., 2023) and video identity masking (Li et al., 2023), have been implemented in prior SSLA studies to minimize such issues (Saquib et al., 2018; An et al., 2018; Mallavarapu et al., 2022), future studies should investigate methods that protect individuals' privacy when data de-identification is not feasible (e.g., providing personalized feedback). Additionally, the use of SSLA for predictive modelling (e.g., Yan, Martinez-Maldonado, Gallo Cordoba, et al., 2022) is also subject to potential risks of biases (e.g., lowering individuals' self-esteem), especially when labelling is used to characterize individuals into different categories (e.g., "low-performing"). Future studies should explore and establish models and guidelines to address these ethical and privacy issues in SSLA. Lastly, balancing human control and automation is also essential to ensure the trustworthiness of SSLA innovations. Future studies should develop or integrate existing trustworthy frameworks (e.g., the Human-Centered Artificial Intelligence framework (Shneiderman, 2020)) into their research and prototypes of SSLA innovations.

5. Discussion

This study systematically reviewed 25 SSLA studies regarding the prominent theoretical and empirical foundations (RQ1), learning contexts, sensing technologies, socio-spatial behaviour, educational constructs (RQ2), opportunities for supporting future educational research and practice (RQ3), and practical and ethical challenges that need to be addressed (RQ4). The findings related to each research question are discussed in this section.

5.1 Research Questions

For the first research question (RQ1), we have shown that the prominent theoretical and empirical works that have influenced the development of SSLA can be categorized into three types, including prior works on SSLA, theoretical foundations, and conceptual or review works (Table 2). The finding that the most prominent theoretical works are related to Hall's groundbreaking work on the theory of proxemics suggested that SSLA research draws its foundations not only from educational theories (e.g., social constructivism) but also from sociology and cultural anthropology. This finding resonates with the call by Knight and Buckingham Shum (2017) for learning analytics research to go beyond traditional educational theories to explore the potential of computational intelligence and technologies in supporting future research and practices. The advancement in SSLA could potentially be a successful example of such endeavours. On the other hand, the citation behaviours between different SSLA research studies could potentially indicate a thriving research community where the authors are familiar with and acknowledge each other's contributions (Dawson et al., 2014). This finding could also indicate a small community of researchers involved in SSLA research, and this area is still in the early stages of its development.

In terms of the second research question (RQ2), we have identified and elaborated on the learning contexts, sensing technologies, socio-spatial behaviours, and educational constructs investigated in prior studies. The clear flow from learning contexts to educational constructs (as shown in Figure 2) indicates that SSLA adheres to the overarching goal of learning analytics, that is, generating meaningful insights about knowledge, teaching, and learning (Gašević et al., 2015; Lang et al., 2022). This alignment is critical for SSLA to remain educationally meaningful instead of merely being a complex combination of ubiquitous computing and data mining techniques that has no foreseeable impacts on actual teaching and learning practice (Dawson et al., 2019; Cukurova et al., 2020). The current findings also hinted at the appropriateness of SSLA in collaborative and interactive learning scenarios, because most of the socio-spatial behaviours and education constructs captured in prior studies involve extensive interactions and physical movements.

For RQ3, we have summarized five opportunities that SSLA offers to support future educational research and practice. These findings, specifically the opportunities for developing novel theories, resonate with the learning analytics cycle (Clow, 2012), emphasizing the importance of completing the learning analytics loop by updating theoretical foundations with empirical findings. Such opportunities are especially important for advancing SSLA because it is heavily context dependent, where the meaning behind socio-spatial behaviours is subject to the changes in learning designs (Yan, Martinez-Maldonado, Zhao, Dix, et al., 2023; Mallavarapu et al., 2022). Consequently, developing context-sensitive proxemics theory could benefit future SSLA research, especially in building robust predictive models without adopting a generalized approach (Gašević et al., 2016).

Regarding the final research question (RQ4), we have identified several practical challenges after assessing the technological readiness and transparency of existing SSLA studies. Specifically, there is an urgent need for future SSLA studies to deploy and integrate their innovations within teaching and learning practices, because most of the existing works relied merely on post hoc evaluation. Such integration could uncover additional insights about willingness to adopt and potential unexpected impacts on different educational stakeholders. This finding resonates with the practical issues surrounding multimodal learning analytics studies (Yan, Zhao, et al., 2022). Adopting a human-centred approach is also vital for improving system transparency and ensuring that SSLA innovations are transparent to teachers and students, which resonates with the growing importance of human-centred learning analytics (Buckingham Shum et al., 2019). Finally, the range of privacy and ethical issues identified in prior studies emphasizes the need for future studies to develop ethics guidelines and tools that protect and empower stakeholders with their rights (Alwahaby et al., 2022).

5.2 Implications

The findings have several implications for supporting learning analytics and SSLA research and practice. First, the detailed summary presented in this review could provide new research methodologies and ideas to researchers who are currently working in or interested in co-located collaborative learning spaces, especially if they want to investigate educational constructs that are socially and spatially relevant (e.g., spatial pedagogy and team dynamics). Likewise, the descriptive and citation network results also provide a clear direction for researchers from different areas to quickly familiarize themselves with the prominent theories and methodologies used in SSLA. Collaboration opportunities could also be sparked between scholars within and outside SSLA research. The synthesized opportunities could inspire SSLA researchers to explore different directions on how their innovations could benefit future educational research and practice. Finally, the identified challenges could motivate and direct future SSLA studies to address these prevalent issues, which may hinder the future development of SSLA.

5.3 Limitations and Future Directions

The current findings are subject to the following limitations. These findings are summarized based on SSLA publications written in English, which may omit emerging works from research communities with a different primary language (e.g., the Spanish research community). Additionally, we only reviewed full-length peer-reviewed publications based on the best review practice from the PRISMA protocol. We omitted interesting works published as short, workshop, or poster papers, considering the early stage of SSLA research. Finally, we did not get into the technical details of SSLA research, which is not the focus of this review but is also essential for developing this research area, because innovations in affordable hardware are also coming out of prior studies (Saquib et al., 2018; An et al., 2018). Future studies could summarize and elaborate on the technical details of SSLA innovations to support the general audience's comprehension. Conceptual and methodological frameworks can also be developed to structuralize SSLA because there is already a variety of essential components (as shown in Figure 2) to integrate.

6. Conclusion

This study presents a systematic literature review of 25 prior studies to make the current progress, opportunities, and challenges of SSLA visible to learning analytics and other educational research communities. We have summarized the prominent theoretical and empirical works and essential components of SSLA research. We have also synthesized the potential of SSLA in supporting future educational research and practice into five clear directions of opportunities. Practical and ethical challenges were also identified for future studies to tackle. Through these opportunities and the ongoing efforts of the contributors, SSLA could be one of the key factors in fulfilling the promises of learning analytics in generating meaningful insights about knowledge, teaching, and learning in co-located collaborative learning spaces.

Declaration of Conflicting Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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