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The i-SUN process to use social learning analytics: a conceptual framework to research online learning interaction supported by social presence

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Interaction is an essential element of online learning and researchers had use Social Learning Analytics (SLA) to understand the characteristics of meaningful interaction. While the potential for network analysis in education (i.e., SLA) is valuable, limited research has considered how best to use this emerging field to inform meaningful interaction in online settings. Online learning researchers need a concise and simplified framework for SLA to support interaction in online learning environments. Therefore, we present a conceptual framework to make SLA accessible for researchers investigating learners' interactions in online learning. The framework includes concepts from network theory and the online learning literature integrated into a new perspective to analyze learners' online behaviors and interactions. We analyzed existing models and frameworks to show how network analysis has been used in online learning resulting in a conceptual environment to investigate learner interaction. The proposed i-SUN framework has four main steps: (1) interaction, (2) social presence alignment, (3) unit of analysis definition, and (4) network statistics and inferential analysis selection. We also identified five ways in which the i-SUN model contributes to the advancement of SLA in online interaction research and provide recommendations for empirical validation. As part of a sequence of manuscripts, we seek to offer a unique perspective to online learning researchers and practitioners by focusing on the social and pedagogical implications of applying network analysis to understand online learning interaction.

KEYWORDS

interaction, social presence, social learning analytics, network analysis, conceptual framework, online learning, distance education, social network analysis (SNA)

1. Introduction

Although online learning has been established as an effective learning mode compared to face-to-face learning (Pei and Wu, 2019), challenges to facilitating online learning persist. Instructors and learners perceive difficulties in meaningfully connecting with one another, establishing an effective presence, and developing communication strategies that support intentional relationships, and eventually, learning (Richardson et al., 2015). As learning is generally considered a social activity (Vygotsky, 1978b; Bruner, 1990; Bandura, 2002; Lowyck, 2014), these challenges can greatly impact student success in online environments.

Learning analytics (LA) has been one way in which researchers consider the effectiveness of online learners' interactions in supporting student success by combining education and data science to inform instructional design (Ifenthaler and Yau, 2020).

The social nature of learning demands external support (i.e., scaffolding; Wood et al., 1976; Vygotsky, 1978a) and interaction (Moore, 1989) among instructors, peers, or the learning environment. Yet, the assumptions of traditional statistical analysis (i.e., independence of observations) limit research questions and can be misaligned with the interdependency that emerges in online learning. As a result, Social Learning Analytics (SLA) has emerged as a sub-field of LA, offering educators and researchers new opportunities for analyzing learning interactions from a perspective that reflects the interdependent nature of learning. SLA focuses on "understanding connectivity and the development of social relationships, and how this can be used to promote learning through social interaction" (De Laat and Prinsen, 2014). Ferguson and Buckingham Ferguson and Shum, 2012 explain that SLA is a socio-constructivist approach to learning analytics in which learning occurs through interaction and collaboration. However, previous research on interaction in online learning using SLA has relied primarily on descriptive analysis rather than inferential SLA (Jan et al., 2019). Inferential SLA analysis allows researchers to estimate learners' interactions over time (e.g., Zhang et al., 2016; Poquet and Jovanovic, 2020; Castellanos-Reyes, 2021) or statistically compare different types of learner networks (e.g., Kellogg et al., 2014). Nevertheless, SLA faces the interdisciplinary challenge of bridging the social network analysis field that rooted in graph theory and sociology with the educational research field. Lack of rigor in the implementation of SLA results in unsystematic reporting of network measures without sound theoretical foundation on what they mean within the learning context resembling to what Poquet and Joksimovic (2022) call a "cacophony of networks."

Methodological approaches that acknowledge the social nature of learning are not enough to support meaningful connections in online learning because they lack the theoretical guidelines to identify which interactions are relevant for establishing a sense of community. Researchers and practitioners have used the social presence construct to understand affective interactions in online learning environments and design online learning experiences that foster such interactions (Fiock, 2020). Social presence posits those members of an online learning community can project themselves as real to others in the online environment (Swan, 2021). Traditionally, social presence interactions have been analyzed from a learner-learner point of view for mutual construction of meaning (e.g., Kyei-Blankson et al., 2019; Castellanos-Reyes, 2021; Lim, 2023). Yet, online learning environments allow for other types of interaction like those between learners and instructors, learners and content (Moore, 1989), learners and network (i.e., social media) (Dennen, 2013), and learners and the rules that govern the broader community (e.g., netiquette, curricula, institutional guidelines) (Jonassen and Rohrer-Murphy, 1999; Engeström, 2001; Yamagata-Lynch, 2010). It is the coherence between the methodological approach, in this case SLA, and the theoretical perspective of social presence that supports educational researchers to draw rigorous and sound conclusions. Thus, it is urgent to have guidelines for online learning researchers conducting SLA that are theoretically sound and contextualized to the complexity of distance education.

While the potential for using SLA and network analysis methods to investigate learning is great, limited research has considered how best to use this emerging field to inform evidence-based practices in online settings. Furthermore, existing frameworks on SLA in online learning focus only on learner-learner interaction to form online communities (e.g., Jan and Vlachopoulos, 2019) without accounting for other types of interaction like learner-interface. For example, collaborative annotation of textbooks for community development (Sun et al., 2023) or intelligent tutoring systems (Ebadi and Amini, 2022). One potential reason for limited research in this area is a lack of conceptual frameworks that can be used to guide the implementation of SLA and a subsequent robust research process. Online learning researchers and practitioners need a concise and simplified SLA framework to support interaction in online learning environments.

The multiplicity of network analysis terms combined with the lack of theoretical integration of online learning interaction and social presence theory compounds the challenge of implementing SLA. In response to the call for "refinement and rigor" in SLA (Poquet and Joksimovic, 2022), we propose a conceptual framework for educators and researchers to understand online learning interaction through SLA and social presence. To guide the development of this framework, we used concepts from communication networks theory and online learning literature integrated into a new perspective to analyze and assess learners' online behaviors and interactions. We first synthesize and critically evaluate the existing literature about SLA frameworks and interaction frameworks in relation to social presence. Then, we provide specific network analysis indicators for researching interaction from a social presence perspective. Next, we discuss the benefits and challenges of implementing the proposed SLA conceptual framework to investigate online learning interaction. Finally, we provide suggestions for future research that could serve as guidelines in this area for researchers.

2. Literature review

The literature review section is divided into five main sections. First, we define social presence in the online learning context. Then, we evaluate the foundational interaction theories and frameworks for online learning in the light of social presence. In the third section, we address recent frameworks in SLA specific to online learning. The last two sections include a table synthesizing the relationship between the frameworks and social presence to support SLA while providing recommendations on how research can use SLA measures.

2.1. Social presence in online learning

Grounding in the telecommunications field (Short et al., 1976), Gunawardena and Zittle (1997) introduced social presence to distance education as "the degree to which a person is perceived as *real* in mediated communication" (p. 9). This definition has been increasingly used in the online learning field by practitioners and researchers alike (Castellanos-Reyes, 2020) and incorporated as part of the Community of Inquiry (CoI) framework. The CoI is a constructivist process-model that describes the components of an online learning experience (Garrison, 2017a; Swan, 2021). Since its inclusion as part of the CoI, social presence has been widely used to research online learning and guide the design of high-quality learning experiences (Fiock, 2020). Nevertheless, the conceptualization of social presence among researchers is not without controversy. For example, Kreijns et al. (2022) challenged the conceptualization of social presence, arguing that researchers confound the social presence's definition with the technology affordances and the interpersonal connections among students.

Despite the definition of social presence being widely debated (Kreijns et al., 2022; Shea et al., 2022), we adhere to the definition of social presence as the extent to which online learners perceive themselves and others as "real people" (Garrison et al., 2000; Rourke et al., 2001; Shea et al., 2022). Social presence is theorized to include three components: open communication (e.g., replying on a discussion board), affective communication (e.g., expressing emotions or liking others' work), and cohesive responses (i.e., addressing peers by name) (Garrison, 2017b; Shea et al., 2022). Social presence is essential in online learning because it influences student satisfaction (Richardson et al., 2017) and performance (Garrison and Arbaugh, 2007; Cui et al., 2013; Joksimović et al., 2015). Social presence has been used to explain interaction in computer-mediated environments, for example, interactions among members of an online community and their interactions with the course activities in the learning experience (i.e., "meet your classmates" activity, discussion board, reading assignments) (Richardson and Swan, 2003).

2.2. Models of online learning interaction and their limitations

In this section, we surveyed prominent models of online learning interaction frameworks as indicated by the Handbook of Distance Education (Dennen, 2019). We reviewed three foundational interactions theories and frameworks in relation to online learning. First, Moore's theory of transactional distance (1998) because of its longstanding history to explain distance learning interaction (Bernard et al., 2009). Second, the Interaction Analysis Model (IAM) (Gunawardena et al., 1997) because it was conceptualized on text-based communication which was the foundation of distance education delivery (Stewart et al., 2023). Third, we introduce activity theory, which was initially conceptualized to understand complex learning environments. Although activity theory was conceptualized for traditional in-person education (Jonassen and Rohrer-Murphy, 1999; Engeström, 2001; Yamagata-Lynch, 2010). Dennen (2019) contextualized the theory to online learning environments, offering a framework for considering additional elements of the distance learning ecosystem. We guide our review based on the social presence construct. Table 1 synthesizes this section.

2.2.1. Moore's theory of transactional distance (1993)

Moore's theory aimed to explicitly identify interaction and clarify traditionally vague and ambiguous concepts such as distance, independence, and interaction (1989). Moore explained that transactional distance referred to the psychological and communications space that separates the learner and the instructor (Moore, 1993). Moore (1993) formulated the concept of transactional distance as a function of dialogue, instructional structure, and learners' autonomy. Further, he explained that transactional distance is greater in pre-recorded sessions with little learner-instructor dialogue, but internal dialogue among learners is greater. Conversely, transactional distance reduces in instructional programs designed as live virtual meetings where there's a two-way interaction between learners and instructors, with less structure and more learner-instructor dialogue. Based on this, Moore proposed three main types of interaction: learner-content, learner-instructor, and learner-learner interaction (1989). There is a need to balance the kind of interaction based on the learner's capacity and needs, the instructors' teaching philosophy, and the nature of the subject (Moore, 1993; Falloon, 2011). Scholars have expanded Moore's original concept of transactional distance to include the interaction between learner and the interface (Hillman et al., 1994) and learner and the network (Dennen, 2013). Specifically, learner-network interactions refer to those behaviors that occur external to the class environment (Dennen, 2019) like communicating with others outside the class who might share similar interests or expertise (Dennen, 2013).

Moore's theory does not address the affective and cohesive components of social presence. Instead, it adopts a learner-centered approach as a focus. In other words, how the individual learner interacts with content, instructor, and other learners, almost singularly or in a linear fashion. Such linearity restricts the complexity of an online learning experience, especially one that includes multiple means of communication. Moore (1993) acknowledges that highly interactive media allow for more intensive and dynamic dialogue. The social presence construct is a helpful lens to evaluate Moore's theory because it includes a community aspect that allows for a more dynamic and complex explanation of interaction in online learning.

2.2.2. Gunawardena et al. (1997) interaction analysis model

Gunawardena et al. (1997) made the case that quantitative participation analysis and self-reported satisfaction within an online learning conference environment are not sufficient for determining the quality of interaction and the quality of the learning experience. As such, they proposed content analysis or interaction analysis of transcripts as being essential to evaluating the quality of interaction. Interaction in this model (Gunawardena et al., 1997) is rooted in the learning sciences in the work of Jordan and Henderson (1995), who described interaction analysis as human-human interaction and human interaction with objects

TABLE 1 Models of online learning interaction and their limitations.

Theory/model name	Interaction constructs	Limitations
Transactional Distance (Moore, 1989; Hillman et al., 1994; Dennen, 2013)	Learner-learner, learner-instructor, learner-content, learner-interface, learner-network.	• Quantification of distance (no scale or qualitative description) • Limited/empirical evidence to support (Reyes, 2013) despite previous meta-analysis (Bernard et al., 2009). • Lack of specificity in theoretical foundations/philosophical foundations and how this is later applied (Goel et al., 2012)
Interaction Analysis Model (Gunawardena et al., 1997)	Five phases: I. Sharing/comparing information II. Discovery of dissonance III. Negotiation and meaning IV. Testing and modification of synthesis V. Agreement statement(s)	• It is limited to mutual communication and co-creation of knowledge (i.e., discussion boards). • Role of instructor not apparent. • Assumes uniform construction of knowledge "quilt" as perceived by evaluator; does not define how to evaluate overall knowledge construction (despite the assumption that multiple versions of knowledge exist among participants). • It does not consider multiple media types and interactivity inherent in modern media.
Activity Theory (Engeström, 1987; Yamagata-Lynch, 2010)	Tension among: Subject (learner), Tools, Rules, and Community (e.g., students, instructors) Division of labor.	• Qualitative focus to research complex systems. • There is room for ambiguous interpretation of the components of activity theory, possibly due to translation of terminology and "conflicting schools of thought" (Bedny and Karwowski, 2004, p. 135).

in their environment. Interaction is, therefore, an "ongoing social process" in which people collaborate, learn, and recognize what they have learned (Gunawardena et al., 1997, p. 403). There is not hierarchical relationship among participants in this model, and therefore, it is not teacher centered. Here, participants are equal in the hierarchy. Interaction is also viewed as informal and voluntary as the learning process naturally unfolds among participants, as a co-creative process rather than an assessment of student performance. Ultimately, interaction is described as a "totality of interconnected and mutually-responsive messages… 'interaction' is the entire gestalt formed by the online communications among the participants...in relation to each other and in a manner which reflects each other's presence and influence" (Gunawardena et al., 1997, p. 407). Gunawardena (1995) adopts a multi-constructed approach to social presence in describing how important and "real" a person "feels" in mediated communication through intimacy (e.g., eye contact, nonverbal cues) and immediacy (e.g., psychological distance, relatability). In relation to the Interaction Analysis Model, social presence is a potential predictor that influences learning outcomes positively. However, interaction is not reflected between the learner and the content, nor is the relationship between the learner and the interface highlighted.

2.2.3. Activity theory in online learning

Activity theory allows researchers to explore learning as an activity system and describes the elements that influence learning (Dennen, 2019). Activity systems "support a systematic and systemic approach to understanding human activities and interactions in real-world complex environments" (Yamagata-Lynch, 2010, p. 1). In activity theory, complex learning environments are conceptualized as "natural situations where multiple individuals are involved in shared activities within a single or multi-organized context" (Yamagata-Lynch, 2010, p. viii). Originating from Vygotskys' theoretical perspective, activity theory was developed by Egeström and later adapted to the educational context by Yamata-Lynch (Dennen, 2019). Engeström (1987) represented activity theory with a triangular model in which the vertices show the components of the complex system, and the sides, the tensions among them.

Despite activity theory being originally conceptualized to understand organizational change in educational contexts from a systemic perspective and to guide the design of constructivist learning environments (Yamagata-Lynch, 2010). Dennen (2019) explained that "activity theory encourages the view that online classes are complex ecosystems" (p. 252) in which tension among parts prompts learning. The online learning activity system framework comprises tools, rules, a community (e.g., students, instructors), and a division of labor (see Figure 1). Yet, the main subject of the system is the student, and the expected outcome is learning (Dennen, 2019). Activity theory allows researchers to comprehensively account for online learning elements (Dennen, 2019). It gives researchers conceptual tools to understand the interconnections among components of the complex system (e.g., learners, instructors, administrators) and their networks of interaction (as well as the juxtapositions of their objects (i.e., outcomes). One of the limitations of activity theory is that its methodologies are focused on qualitative research, mainly because it is through qualitative inquiry that researchers can deeply understand the complexity of a learning system. Furthermore, Bedny and Karwowski (2004) argue that researchers' interpretation of the components of activity theory is ambiguous due to translation challenges and "conflicting schools of thought" (p. 135). The diverse interpretations have obscured the use of activity theory challenging researchers to use to explain learning. Yet, we posit that activity theory serves as an analytical framework to better reflect the potential of SLA in online learning interaction. Unlike earlier LA methodologies that rely on quantitative data, new methods that involve SLA (e.g., Social Epistemic Network Signature, Gašević et al., 2019) are not limited to quantitative data.

This framework considers social presence in terms of affective association and instructor investment since it explores

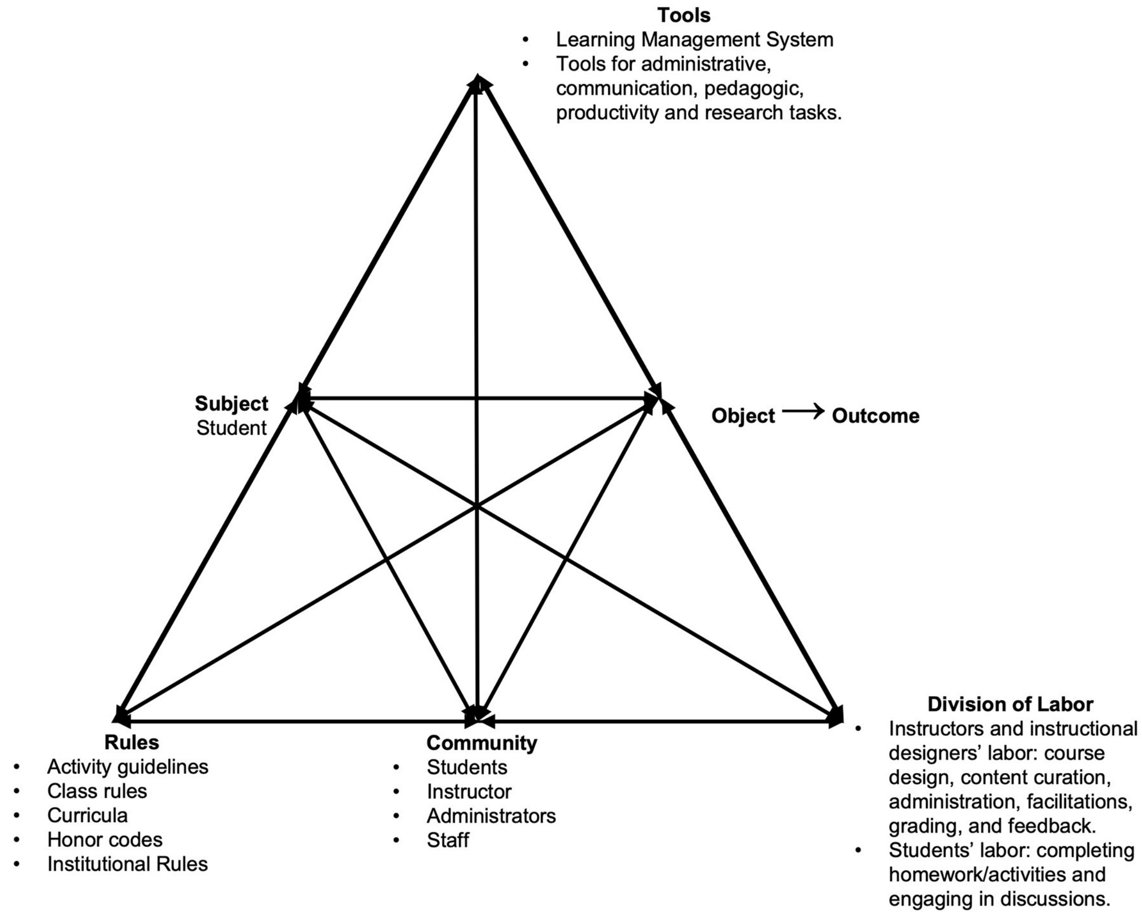

FIGURE 1
Adapted representation of Dennen's (2013) online learning as an activity system.

learners' and instructors' individual and group constructs through interrelationships between tools, the subject, rules, community, and division of labor. However, the main gap exists in exploring the interface's functionality and how social presence is enabled in online environments through interaction intensity, cohesion within the community, and how affective outcomes are achieved. As such, exploration is needed to consider how the individual, and by extension, communities of learners interact with the interface to achieve the outcomes.

2.2.4. Limitations across interaction theories

The theory of transactional distance (Moore, 1993) is a valuable framework for examining interactions among online learners, their instructors, and the content, while activity theory (Engeström, 1987) is much broader and explores a systematic interplay of "tools, rules, people, and work" (p. 254) that comprise the online learning ecosystem. Within the traditional conceptualization of online learning (Stewart et al., 2023), the way people interact via text-based communication leads to an exchange of cultural insights, which in turn ignite knowledge as a collective social construction (Gunawardena et al., 1997; Gunawardena, 2013).

We propose that existing interaction theories do not fully reflect the complexity of online learning. On the one hand, transactional theory (Moore, 1989, 1993) focuses on interpersonal interaction and interaction with content. However, it does not include the interaction and tensions between other members of the online learning community (i.e., administrators and staff) and the available tools for online learning (i.e., learning management systems, external technology). On the other hand, the Interaction Analysis Model (Gunawardena et al., 1997) does not consider the interaction between the learner and the interface, as well as the learner and content. Furthermore, it relies on text-based interaction a as means of knowledge construction in online education. Yet, the adoption of Emergency Remote Teaching (ERT) (Hodges et al., 2020), leveraged synchronous communication as part of the response to the COVID-19 pandemic and the sustained and generalized use after (Stewart et al., 2023) showed the need to include other forms of delivery and interaction beyond text-based communication as central elements of online education. Finally, activity theory in online learning (Engeström, 1987; Yamagata-Lynch, 2010) presents a holistic, rich, qualitative approach to understanding interaction as a complex interrelation among learners, communities, tools, objects, and subjects. Still, there is a need to integrate facets of the online environment and how it affords interaction by including the online learning interface and other online interaction elements (i.e., network, rules, community) using SLA concepts. Therefore, the focus here is to share a conceptual framework that comprehensively reflects the interactions in online learning at (1) an interpersonal level and (2) the larger learning environment, while accounting for the potential of SLA and network analysis supported by the social presence construct.

2.3. Social learning analytics for online learning

Ifenthaler (2015, p. 447) defines LA as "the use, assessment, elicitation and analysis of static and dynamic information about learners and learning environments, for the real-time modeling, prediction and optimisation of learning processes, and learning environments, as well as for educational decision making." LA in higher education has primarily focused on supporting student success (Sclater et al., 2016; Ifenthaler and Yau, 2020). For example, LA has been used to predict performance (Xing et al., 2015; Aulck et al., 2017), identify at-risk students (e.g., students who may dropout) (Aguiar et al., 2014; Cohen, 2017), analyze student dropout to support retention (Aguiar et al., 2014), or improve course design, and student engagement (Lockyer and Dawson, 2012). LA for online learning environments primarily uses learners' data (e.g., frequency of LMS logons, course resources downloads, or module accesses) to account for their navigation patterns, preferences, and behaviors (Ifenthaler and Widanapathirana, 2014). However, LA's potential has yet to be realized, as research commonly focuses on aggregated quantitative representations and does not fully consider the social dynamics necessary for meaningful learning in online environments. Furthermore, LA has been described as part of an "algorithmically pervaded society" (p. 17) in which theory has been discarded in place of data analysis (Knight and Buckingham Shum, 2017). Relying only on data analysis results in the under-exploration of the relationship between LA and its application and a lack of understanding of LA among educators and researchers (Drachsler and Greller, 2012). Viberg et al. (2018) found in a literature review on LA in higher education that despite the potential for LA to improve learning practice, very little LA application is realized in higher education practice.

Given that learning is inherently a social activity that requires external support (i.e., scaffolding) and interaction from instructors, peers, or the learning environment; a subfield of LA emerged —Social Learning Analytics (SLA). SLA offers educators and researchers new opportunities to overcome challenges in online teaching and learning like feelings of isolation and community building (Hart, 2012; Richardson et al., 2015) under the assumption that social learning contributes to the "quality of learning and student experiences" (Poquet and Joksimovic, 2022, p. 38). SLA focuses on understanding the interdependency of social relationships and how this can be used to promote learning through social interaction. SLA takes a socio-constructivist approach to learning, in which learning occurs through interaction and collaboration. As a part of SLA, researchers use network analysis to understand learners' interactions (Aviv et al., 2005) in online learning environments (Jan et al., 2019). Network analysis uses statistics and graph theory to study the relationships of entities (e.g., learners), assuming dependency on those with whom they connect and those within the same group (Monge and Contractor, 2003).

2.4. Conceptual frameworks for social learning analytics and their limitations

Next, we analyzed three main conceptual frameworks of SLA. To guide this process, we used the social presence construct to examine SLA frameworks from a perspective relevant to online learning. First, we begin with Ferguson and Shum's (2012) framework that defines the main elements of SLA. We use Buckingham and Shum's SLA framework, which pioneered the identification of the main elements of SLA, because (a) they propose an analytical approach that takes a social learning theory approach, (b) it includes the use of social networks incorporating the network element that Dennen (2019) adds to the transactional distance theory, and (c) it takes a community-centered approach which agrees with the social presence perspective of perceiving and projecting each other as real (Lang et al., 2022). Then, we analyzed Jan and Vlachopoulos's (2019) exploration of the concept of communities based on online discussion boards. Given the historical roots of text-based communication in distance learning, we included Jan and Vlachopoulos's (2019) framework that focuses on discussion boards and capitalizes on the socio-constructivist lens of social presence to apply network analysis to understand learning. Finally, we discuss interaction per Kent and Rechavi's (2020) framework as it pertains to usage in online environments because they account for students who are less active in discussion boards. Kent and Rechavi's (2020) perspective is essential to account for those unobserved interactions in online learning that still foster social presence perceptions. Table 2 synthesizes this section.

2.4.1. Ferguson and Shum (2012)

Ferguson and Shum (2012) recognized the importance of LA in improving learner outcomes, noting great potential arising from an "unprecedented" volume of data about learner activities and interests. Within a learning design space, the authors propose that SLA should be implemented to distinguish the concept and unique features of a social learning environment. Ferguson and Shum (2012) also suggested the need for defining the possibilities of SLA; as being inherently social (as a behavior and discourse analysis) or socialized (as an application to a broader setting; content, disposition, and context). Finally, the applications of SLA demand an ethical perspective by considering its limitations and abuses.

The underlying socio-cultural philosophy of Buckingham Shum and Ferguson draws on the distinction that SLA is a unique subset of LA that rests on the premise that novel skills and ideas

TABLE 2 Conceptual frameworks for social learning analytics and their limitations.

Conceptual framework	Constructs	Type of interaction	Social network statistics*	Limitations based on social presence
Ferguson and Shum (2012)	Social analytics and socialized analytics Five conditions influence learning	Social engagement direct interaction (dialogue) (learner-learner interaction) and indirect interaction (ratings, recommendations, reactions) (learner-interface, learner-content)	Actors: People/resources. (Actors are also known as nodes). Ties: Relations among actors. Weak ties: Accessing new knowledge and informal learning. Strong ties: Deepen knowledge. Egocentric: Individual perspective/Individuals who support the online learner. Whole network: Group of online learners/Individuals who hold the network together.	Affective communication and cohesive responses are not considered from a network analysis perspective.
Integrated Methodological Framework (Jan and Vlachopoulos, 2019)	SNA Parameters Application Adaptation Interpretation	Community focus CoI/CoP. learner-learner interaction	Cohesion: Group of network analysis measures to understand whole networks of learners. The measures included are: density, average degree, centralization, components, and core-periphery structure. Sub-groups: To investigate groups of students using the *cliques* measure. Cliques represent a subgroup of actors (e.g., learners or messages) in which all are related among themselves. Power Dynamics: Group of network analysis measures focused at the individual (i.e., actor) level. The measures included are: Reciprocity, redundancy, transitivity, and centrality (degree/indegree/outdegree).	Researchers might find it challenging to apply the IMF because it integrates multiple concepts of both Community of Inquiry and Community of Practice. Yet, it does not go into detail on the subconstructs of either of them.
Kent and Rechavi (2020)	Creative interaction network Consumption interaction network Organizational interaction network	Community, content, and meta-cognitive	Distance: It focuses on how tightly connected are the interactions among participants. They use the statistics *diameter* to account for the shortest path that connects the farthest members of a community. Reciprocal: If focuses on peer-learning, collaboration, and collective construction of meaning using the *reciprocity* (i.e., mutual interaction) and *transitivity* (i.e., how two interacting actors influence the third one) network statistics. Influence: The extent to which an actor is central in the community using the out-degree (i.e., outgoing interactions) and betweenness statistics (i.e., interactions with essential nodes in the network).	Lack of indicators to account for affective communication.

*This table portrays the authors' definitions of SNA measures. These are dependent on each framework as network analysis allows for great flexibility to account for individual contexts.

are a result of interaction and collaboration. The authors maintain that five conditions or phenomena influence the learning context: (1) technology, (2) open access, (3) knowledge age skills, (4) social learning as a catalyst for innovation, and (5) challenges to educational institutions.

Social learning is characterized by "changing affordances" in which social activity occurs "at a distance, in mediated forms" (Ferguson and Shum, 2012, p. 8). Social learning occurs when intentions are clarified, learning is grounded, and learners are engaged in conversations to increase their understanding. Ferguson and Shum (2012) refined the conceptualization of SLA by specifying a five levels taxonomy: social network analytics, discourse analytics, content analytics, disposition analytics, and context analytics. From the social presence perspective, Buckingham Shum and Ferguson account only for the open communication element when addressing network analysis in SLA to investigate learners' interactions and relationship development, without considering affective communication or cohesive responses.

2.4.2. Jan and Vlachopoulos (2019)–Integrated methodological framework

Jan and Vlachopoulos (2019) proposed an Integrated Methodological Framework (IMF) that combines Community of Inquiry (CoI) and Community of Practice (CoP) frameworks through the lenses of SLA. The CoI is a constructivist process-model for collaborative discourse that integrates three "presences" that constitute a successful online learning experience (Garrison et al., 2000; Swan, 2021)–among those presences is *social presence*. A CoP includes a group of people with shared interests and different levels of expertise and interest in a shared domain (Wenger, 1998, 2004; Farnsworth et al., 2016) that relates closely to informal and professional learning experiences (Dennen, 2019). Although CoI and CoP differ in participants' expected level of commitment and participation–in which the former expects higher commitment and the latter encourages more autonomy–both are forms of collaborative and interdependent online learning (Dennen, 2019). After conducting a systematic review of research that investigated CoI/CoP through social network analysis, Jan et al. (2019) found the need to provide a conceptual framework to guide the identification of online learning communities. They argue that all communities are networks, and therefore, an SLA approach is appropriate. Their purpose is to build a framework to identify learning communities in higher education online learning. Jan and Vlachopoulos (2019) argue that there is a lack of quantitative research using both CoP and CoI frameworks, which are widely used in online learning (Castellanos-Reyes, 2020). Despite the potential of SLA to identify online communities, little research exists considering CoP and CoI through SLA. Although, to our knowledge, Jan and Vlachopoulos (2019) are the pioneers of proposing a conceptual framework that integrates online learning theory and SLA, their SLA approach is still descriptive, limiting researchers' possibilities. For instance, they focus on descriptive aggregated network analysis, leaving behind inferential analysis (e.g., exponential random graph models). Narrowing down Jan and Vlachopoulos's (2019) approach from all the constructs of CoI and CoP to social presence would better serve researchers investigating interactions in online learning using SLA given the potential complexity of network analysis.

2.4.3. Kent and Rechavi (2020)—Deconstructing online social learning

Like Jan and Vlachopoulos (2019) and Kent and Rechavi (2020) also focused on the potential of SLA to support online discussions from a community perspective. Kent and Rechavi advocate for more types of interactions apart from "speaking" interactions (e.g., direct communication via discussion board posts). They explain that a majority of participants in online learning are considered *inactive* or *passive*. Therefore, suggesting speaking interactions as the most valid type of interaction is a misconception because learners also engage in other behaviors like interacting with content. Furthermore, discussion boards elicit anxious feelings in learners who doubt the significance of their contributions (Koehler and Meech, 2022). Guided by a collaborative learning paradigm, Kent and Rechavi (2020) describe the learners' interaction networks in online communities based on three types of interactions: (1) creational, (2) consumption, and (3) organizational. Kent and Rechavi (2020) allegorize creational interactions as "digitally speaking," implying proactive interactions from learners (e.g., posting, editing posts). "Digitally listening" exemplifies consumption interactions like following peers, watching videos, or reading. The authors argue that learners' consuming interactions are usually overlooked due to the complexity of data extraction and an over-emphasis on individual assessment rather than collaborative work. Kent and Rechavi argue that consumption interactions serve to consider passive learners, also known as lurkers. Finally, stemming from Ausubel's advance organizers (1968), learners' activities with content organizational interactions refer to organizing their content through tags and bookmarks. While Kent and Rechavi (2020) include student-content interaction, a more apparent distinction between consuming interaction (i.e., interaction with content) and organization interaction (i.e., sorting content) is needed to better reflect the types of networks that researchers can study through SLA. Furthermore, despite Kent and Rechavi's work addressing learners that are usually overlooked (i.e., lurkers), they fall short on how to analyze the creational content that learners make in their interactions. Furthermore, as social presence is a precursor of a trustworthy environment for knowledge construction, understanding how "digitally listening" (student-content) interactions contribute to this foundation by supporting knowledge construction is necessary. As Richardson and Swan (2003) asserted "social presence permeates not only the activities generally designated as social activities but also those activities usually designated as individual activities" (p. 80). Furthermore, the SNA measures they examined, like transitivity and betweenness, can be related to the social presence construct "group cohesion" because they estimate how a network of learners is well connected. Such are summary statistics that describe the interactions within the network. Still, they do not account for students' perceptions of the social presence or their ability to display themselves as real. We ask, what aspects of the creational interactions that Kent and Rechavi propose make learners feel part of an online community to learn socially? Specifically, we suggest that adding the perspective of affective communication from the social presence construct is much needed to understand online learning interaction deeply. For example, include indicators that account for students' feelings during discussion boards or when interacting with the content.

3. Defining the i-SUN conceptual framework

The above models and frameworks demonstrate that interaction is a critical aspect of collaborative online learning and, consequently, of social presence to sustain online learning. Aside from learning occurring individually (Anderson, 2003), accounting for social presence enhances online learners' experiences and interactions by positively influencing their perceived learning and satisfaction (Richardson et al., 2017). As such, interaction can be among learners, instructors, content (Moore, 1989); learner and the interface (Hillman et al., 1994); and even between learner and the network (Dennen, 2013). We also underscore the need to account for the interaction of online learners who do not interact directly with peers or instructors (Kent and Rechavi, 2020)-in other words, who prefer to interact with the interface, the content, or the network only. Previous work described the unique role of discourse as essential to examining the quality of the interactions within the online learning experience (Gunawardena et al., 1997). As explained by Dennen (2019), Engeström captures the complexity of online ecosystems by describing tensions among elements. Taking all these perspectives together, we propose using a network analysis lens to help researchers explain the complexity of interactions in online learning on what is called SLA (e.g., Ferguson and Shum, 2012; Jan and Vlachopoulos, 2019). We posit an integration of social presence, SLA, and network analysis to research online learning interaction. To that end, we first offer a visualization of the proposed steps to research online learning interaction using SLA through the i-SUN process (see Figure 1). Then, we address the indicators of SLA measures for researchers to investigate online learning interaction through SLA and the social presence construct lens (Table 3).

TABLE 3 Social learning analytics indicators to research interaction from a social presence perspective.

Social presence category	Activity system component involved[a]	Interaction type	Examples of network analysis indicators[b]
Affective communication	Subject, community, tools	L-L, L-I, L-C	*Degree measures*: Incoming (i.e., indegree) and outgoing (i.e., outdegree) interactions among learners, between learner and instructor, and learner and content: • Reacting to peers through system buttons (e.g., like, dislike) (e.g., Castellanos-Reyes, 2021)
	Subject, community,	L-L, L-I	*Reciprocity*: The extent to which affective communication is mutual. • Reacting back to peers through system buttons (e.g., like, dislike) (e.g., Castellanos-Reyes, 2021)
	Subject, community, tools	L-L, L-I, L-C	*Isolate:* Learners with no affective interaction received or sent in the network
Open communication	Subject, community	L-I	*Betweenness*: The extent to which the instructor mediates between learners to connect them. • Tagging/Mentioning students as part of a follow-up comment in the discussion board
	Subject, community, tools, division of labor	L-L, L-I	*Isolate:* Learners with no links to peers or the instructor. No reports of opening content, downloading content or sharing content via networks. Serves to spot inactive members of a conversation (e.g., Satar and Akcan, 2018).
	Subject, community	L-L, L-I	*Degree measures*: Incoming (i.e., indegree) and outgoing (i.e., outdegree) interactions among learners and between learner and instructor: • Sending/receiving messages replies in discussion boards. • Identifying degree measures ensures that all parties involved contribute to a collaborative learning experience.
	Subject, community,	L-L, L-I	*Reciprocity*: The extent to which replies in discussion boards are mutual.
	Subject, community	L-L, L-I	*Diameter:* The shortest distance that connects "the farthest users in the community" (Kent and Rechavi, 2020). It serves to identify members of the community that may not share the same ideas.
	Subject, tools, rules	L-Int, L-N	*Transition networks:* Learners' paths and interactions within the system (e.g., Zhu et al., 2016) indicated by clickstream data. • The same network measures apply (reciprocity, degree, isolate, diameter, betweenness, isolate) but steps taken within the system (clicks) rather than individuals or the content. • Clickstream data may help verify learners required access to the platform to complete course requirements.
Cohesive responses	Subject, community, tools, rules	L-L, L-I, L-C	*Epistemic Network Analysis*: Discourse components become units of analysis and nodes of a network. Connections among components are based on co-occurrence (Gašević et al., 2019). • The same network measures apply (reciprocity, degree, isolate, diameter, betweenness, isolate) but among ideas (discourse components) rather than individuals or the interface. • The Integrated Methodological (Gunawardena et al., 1997) framework serves to categorize discourse components.
	Community	L-L, L-I	*Cliques:* Subset of learners that reach each other through interaction. It means that all members of a click have connections among themselves. Cliques can help us identify subgroups in a class in which cohesive responses take place (e.g., Jimoyiannis et al., 2013; Gašević et al., 2019)

L-L, Learner-learner interaction; L-I, Learner-Instructor; L-N, Learner-Network; L-Int, Learner-Interface.
[a]As per activity theory, interaction is the object of the online learning system environment. Given that we account for types of interaction, we are not adding it in the column "Activity System Component."
[b]Definitions of basic network analysis indicators were contextualized to the online learning field.

3.1. The i-SUN process

We propose a four-step process using social learning analytics for researching online learning interaction supported by social presence (Figure 2) with the purpose of fostering rigorous application of online learning theory when using complex data and methods. The first step focuses on choosing the interaction of interest. Second, researchers are suggested to align the social presence subconstruct with the selected interaction to guide their inquiry. Third, based on the previous selections, researchers are prompted to choose the units of analysis, as well as the type of network they would like to research. Finally, a set of descriptive network statistics can be selected to understand the interaction and, if necessary, inferential network analysis tests.

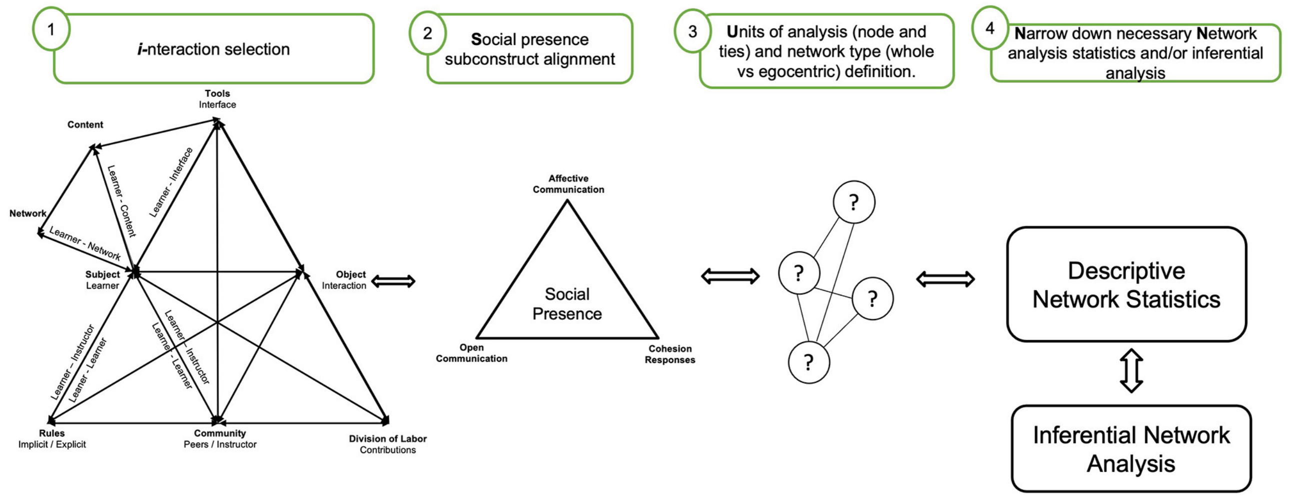

FIGURE 2
The i-SUN process to use social learning analytics to research online learning interaction guided by social presence.

3.1.1. Step 1: i-nteraction selection

The main triangle in Figure 2 depicts the tension between the online learner (i.e., subject) and the complex environment (i.e., tools, object, division of labor, community, and rules) as captured by Engeström's (2001) Activity Theory adapted to online learning (Dennen, 2013). This structure includes the subject who is the student engaged in activities within the online learning system resulting in interaction. Students are the actors or nodes initiating the interaction toward instructors, other learners, content, the interface, and the network (i.e., social media). It is worth noting that the learner-network and the learner-community are not interchangeable, as learner-network interaction refers to interactions with "outsider" individuals (Dennen, 2013) whereas learner-community refers to interactions with those who are a part of the institutional academic community (i.e., instructor and peers). The rules are "Implicit and explicit guidelines that constraint the activity" (Xing et al., 2015). The interface or the instructor could impose these rules. For example, instructors usually enforce implicit rules like netiquette in discussion boards. Explicit rules might include interface affordances to include (or not) liking buttons to acknowledge announcements and comments. Furthermore, ethical considerations about the data gathered for SLA fall within this category. Community involves the interaction between learners and peers and learners and instructors that create a sense of community. Given that direct exchange of information may not be necessary for all learners to establish a sound sense of community. Therefore, the tension between the learner and tools is also relevant. Tools are the instruments that mediate the learning environment (e.g., learning management systems, institutional email).

The two smaller triangles adjacent to the main structure add the components of the network and the content that refer to the interaction between the subject (learner) and the content and the network as proposed by Hillman et al. (1994) and Dennen (2013). The three components (tools, content, and network) are aligned as non-human elements from which SLA gathers data to support online learning interactions. Finally, the object is learning interaction itself with the components of the online learning activity system.

3.1.2. Step 2: social presence subconstructs alignment

After choosing the object of the system, which is the interaction itself, researchers need to align such interaction with at least one of the social presence elements to guide their inquiry. This interaction is supported by the three elements of social presence: open communication, affective communication, and cohesive discourse. Researchers can either use the three components of social presence separately like Tirado-Morueta et al. (2016) did or use the social presence construct as a whole, following the example of Shea et al. (2014). Although researchers are encouraged to use the social presence construct holistically, sometimes, the available interaction data are not comparable to all the elements of social presence, for example, in the case of Castellanos-Reyes (2021), who faced the limitation of using clickstream data to investigate the interaction and consequently focused only on affective communication and open communication.

3.1.3. Step 3: units of analysis and network type definition

This step focuses on defining who are the nodes or actors in the interaction of interest and which type of network better suits that interaction. Most research using SLA so far has focused on learner-learner interaction. Therefore, the nodes in the analysis are the learners themselves. If researchers focus on single online courses, their analysis can use whole networks. In other words, they can study the interactions of the entire system. Researchers can also focus on longitudinal analysis of learners' networks. For example, the work of Saqr and López-Pernas (2021b) who follow the interactions of online students over an entire program.

3.1.4. Step 4: narrow down network analysis statistics and inferential analysis

Although network analysis provides a plethora of network statistics to choose from, researchers would benefit from keeping an efficient rather than extensive attitude toward using network analysis measures. For example, Castellanos-Reyes (2021) used the indegree measure (i.e., the number of incoming interactions received by an actor) to estimate affective and open communication. On the one hand, the number of likes received on a comment on a discussion board was equivalent to affective communication. On the other hand, the number of comments that a student received was operationalized as open communication (Castellanos-Reyes, 2021).

Table 3 integrates the different elements of the proposed framework with specific measures to guide researchers when using SLA to examine online learning interactions. The first column refers to the categories of social presence, while second column refers to the components of the complex activity system that play a role in each social presence element. The third column refers to the type of interaction. Given that SLA uses network analysis measures to explain learners' interactions (Aviv et al., 2005), a central component of the i-SUN framework is to contextualize the definition of basic network statistics frequently used in SLA for online learning. As such, the fourth column refers to the specific SLA measures adapted. The network analysis indicators described stems from theories of communication networks (Monge and Contractor, 2003) and foundational work on social network analysis (Marin and Wellman, 2011). Furthermore, in the fourth column specific examples of each SLA indicators are provided for guidance. Some network analysis measures repeat given that researchers may use one measure to explore different aspects of interaction and social presence. Readers interested in a more detailed description of network analysis measures, please refer to Monge and Contractor (2003) and to Carolan (2014) for contextualization in broader educational research.

4. Discussion and applications

The conceptual framework and indicators presented in this paper will serve researchers who want to understand online learning interactions through SLA. Currently, SLA is dominated by a small group of researchers, and this framework can help create an opportunity for others to join that conversation. Perhaps, one reason for this might be the perceived complexity of the methods used. Therefore, we believe that a conceptual framework may allow other researchers to join this conversation by elaborating on the meaning of standard SLA measures in online learning. This conceptual framework adds value to the field by connecting online learning constructs to network analysis measures used in SLA. Previous researchers have conceptualized network analysis for educational research (Ferguson and Shum, 2012; Jan and Vlachopoulos, 2019; Kent and Rechavi, 2020). However, existing frameworks are still too obscure for researchers unfamiliar with network analysis to follow. Yet, the proposed framework merits consideration, given its focus on a step-by-step basis and its integration of inferential network analysis. Furthermore, we have expanded upon the pioneering work of Jan and Vlachopoulos (2019) by including interactions among members of the community within discussion forums and other elements of the activity system (i.e., content, network, interface).

The presented conceptual framework offers practical guidelines to researchers who foster interaction through social presence. Therefore, the proposed framework may support future endeavors that conceptualize other elements of online learning communities apart from social presence, like cognitive and teaching presence. Future work could expand the proposed framework using the exemplary work of Sadaf and Olesova (2020) who used SLA to explore the Practical Inquiry Model in relation to social presence. Given that the Practical Inquiry Model is used to operationalize cognitive presence, we foresee that future work on SLA and interaction will take upon the challenge of addressing these other constructs. Therefore, the i-SUN model could potentially be applied to other online learning constructs such as cognitive interactions.

4.1. Applications of the i-SUN conceptual framework

We argue that through SLA, network analytic methods are a coherent approach to online learning because they can illuminate the interdependencies of the learning ecosystem. However, the complexity of network measures and their indiscriminate use in educational research poses interpretative challenges for researchers leading to a "cacophony of networks" (Poquet and Joksimovic, 2022). Therefore, this framework does not focus on further analyzing empirical data but rather on "integrating existing perspectives into a more holistic view" (McGregor, 2019, p. 7) that connects the bodies of literature of online learning interaction, SLA, and network analysis. As conceptual frameworks do not generally include empirical data (McGregor, 2019), this framework provides a list of potential applications of the i-SUN Conceptual Framework that merit empirical validation. These examples serve the online learning field as guidelines for rigorous SLA implementation.

4.1.1. Fostering community using task-centered approaches

When learners interact with each other through the interface, active participation is facilitated by achieving common goals through division of labor and open communication. Yet, we recommend studying the specific mechanism and instructional methods that drive such facilitation. A good example is Tirado-Morueta, Maraver-López, Pérez-Rodríguez and Hernando-Gómez (2020) work in which facilitation tasks are explored using network analysis measures (i.e., density and centralization) in the light of social presence. Researchers could integrate instructional elements using Molenda and Subramony's (2021) update of the elements of instruction framework which provides a set of communication configurations that can be explored through SLA and social presence.

4.1.2. Use of learner-network interaction to foster knowledge transfer through egocentric approaches

The addition of learner-network interaction proposed by Dennen (2013) allows researchers to add authentic learning experiences to online learning interactions. For instance, registering learners' interactions with individuals outside the formal online learning community, such as experts on Twitter (Castellanos-Reyes et al., 2021). Suppose researchers are looking to investigate learner-network interaction. In that case, they might not have access to all learners available in the network. So, although the unit of analysis is still learners, they might want to focus on an egocentric approach to online learning. An analysis of egocentric networks, learners are asked for information about those with whom they interact. However, those at the other end of the interaction are not part of the research. A potential application is to ask learners who are the top three Twitter users who make them feel affectively connected to the community.

4.1.3. Go beyond threaded discussion data

Most research using network analysis to examine social presence centers on text-based communication. However, focusing only on discussion boards leaves behind those vicarious learners who benefit from reading without engaging in conversation, the so-called *lurkers* (Sun et al., 2014; Bozkurt et al., 2020). Koehler and Meech (2022) found that discussion boards can overwhelm learners, producing anxiety about what to post and the merit of their thoughts compared to peers' contributions. Furthermore, social presence behaviors might occur in other aspects of the course, like communications via email as part of group work. Again, the vast amount of data collected through learning management systems can enrich researchers' conclusions about students' social presence. For example, researchers might also integrate the Community of Inquiry instrument (Arbaugh et al., 2008), specifically the SP subscale, as covariates of their SLA research. Combining the self-reported measures of SP as covariate measures would shed light on how the network configuration of online learning communities reflects students' internal psychological states. Furthermore, ERT (Hodges et al., 2020) employed widely during the COVID-19 pandemic highlighted other formats of distance education delivery, (e.g., synchronous interaction via videoconference) that should be examined. Although mandatory viewing of pre-recorded lectures and videoconferencing are uncommon in formal distance education (Stewart et al., 2023), they became the heart of ERT, eventually taking an essential role in online learning post-pandemic. Future research could explore the relationship between synchronous communication via videoconferencing and constructs like connectedness and community building (Belt and Lowenthal, 2023), and eventually social presence interactions as the object of the learning experience.

4.1.4. Being intentional with network analysis indicators

Network analysis offers a plethora of network statistics to understand and explain the structure of a network. Furthermore, network analysis allows researchers to define what each statistic means in their contexts. Yet, it does not imply the unsystematic use of statistics for the sake of reporting. Saqr and López-Pernas's (2021a) meta-analysis of network analysis centrality measures used to investigate collaborative learning argue that previous work shoes inconclusive and contradictory results. Their analysis recommends using degree and eigenvector centrality measures as performance indicators but discourage the use of closeness and betweenness centrality. We invite researchers to be intentional about the statistics used in SLA measures, and above all, guide their definitions with a theory like the social presence construct. For example, previous work by Shea et al. (2010, 2013) have suggested that measures like centrality are significantly related to social presence.

4.1.5. Explore correlational and inferential network analysis

The merit of descriptive work is indisputable. It is descriptive analysis and observations what drive researchers to formulate hypotheses to explain the educational phenomenon. Yet, we encourage researchers to make the leap from descriptive SLA to inferential SLA to better understand online interaction and social presence. Inferential SLA does not need to involve complex longitudinal (Castellanos-Reyes, 2021) or epistemic (Gašević et al., 2019) research designs. For instance, parallel to traditional t-tests, researchers could compare two different relations of the same set of learners. For example, researchers could explore if a social presence network obtained from online learners' collaboration shows patterns that deviate from a comparable random network (Borgatti et al., 2018).

4.1.6. Question the boundaries of an online community and who belongs to it

Social presence in online learning is conceptualized in this manuscript from the CoI lens. Although ERT has driven researchers various delivery forms of online learning like synchronous communication through the CoI lens (Shea et al., 2022), the CoI was conceptualized to address text-based computer-mediated communication in formal higher education, which assumes that all students enrolled in a course are members of the community. Nevertheless, issues like passive students or lurkers (Sun et al., 2014; Bozkurt et al., 2020) and the inclusion of intelligent tutoring via artificial intelligence (Ebadi and Amini, 2022; Huang et al., 2022) make us push the question of the boundaries of an online community. Related to the suggested application of going beyond discussion boards, we invite the community to apply the i-SUN process to identify who belongs to an online community by comparing observed data from discussion boards with students' reports on who they consider being in their communities. Taking such an approach might shift the focus to individual students' connections without assuming that the community includes everyone enrolled in a course.

5. Conclusions

There is a need for a SLA taxonomy to analyze online learning interaction that fosters a rigorous application of online learning interaction theory combined with network analysis methods. As such, the expansion of the i-SUN conceptual framework into specific measures used in SLA is a concrete tool for researchers. Future work on SLA should have an intersection and consideration of cultural contexts and nuances. Examples include exploring the relationships between culture and learning through measures such as collective quantitative proficiency. For example, process data collected from computer assessment environments are analyzed through transition networks. Conceptual frameworks require an application to explore how the offered operationalizations stand in a real-world setting. Therefore, future work should focus on how the provided SLA measures reflect online learning interaction. We hope to apply the proposed measures in a prospective case study.

Author contributions

DCR contributed to conceptualization, writing of initial draft, creation of visualization, and reviewing and editing. AK and JR contributed with critical review, and commentary or revision. All authors contributed to the article, manuscript revision, read, and approved the submitted version.

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Conflict of interest

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