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REVIEW

Social Educational Robotics and Learning Analytics: A Scoping Review of an Emerging Field

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Abstract

Social Educational Robotics and Learning Analytics (LA) are prominent fields in technology-enhanced learning, but their combined potential remains underexplored, despite methodological similarities. Increasingly, signs of joint interests have emerged, with a surge in publications mentioning both social robots and learning analytics in the last five years. We therefore conducted a scoping review to explore if a new research field is emerging. We identified 29 empirical studies that combine social robots and LA, but also found that few studies explicitly state that social educational robots and LA are used in combination. Several studies used social educational robots that adapted to the learners or the learning environment based on interaction data. This signifies that they are in fact employing the feedback cycle that is at the core of LA methodology, but as most of these studies update the learner model using post-session data (e.g., learner improvement or feedback), they are long-term studies with repeated interventions that are applying LA methodology inadvertently. There are also benefits for LA research to use social educational robots, since LA increasingly uses an array of equipment to collect multimodal data, and all studies in this review employ at least two input modalities ($\mu = 4.4$). Social robots provide the possibility to collect this data non-intrusively with the robot itself, in addition to creating a pedagogically boosted interaction compared to traditional LA interventions (e.g., learning management systems). By raising researchers' awareness of how close the fields of social educational robotics and LA are, substantial synergy effects could therefore be gained.

Keywords Human-robot interaction · Social robots · Educational robots · Learning analytics

1 Introduction

Despite their common origin within Technology Enhanced Learning (TEL), and appearing at approximately the same time, the two fields of Learning Analytics (LA) and Social Educational Robotics (abbreviated SER in this paper) have steadily grown without much interaction. Recent development, however, suggest that this has started to change and that a new, joint research field may be emerging.

This paper investigates this possibly emerging field suggested in Fig. 1, which we in this paper will call SER-LA (for Social Educational Robots and Learning Analytics) We first introduce the two research fields (Sects. 1.1–1.2) and their possible combination (Sect. 2), before presenting our scoping review of studies that combine SER and LA (Sect. 3), discussing the findings of the review (Sect. 4), and offering our concluding suggestions regarding how synergies between SER and LA may be explored further (Sect. 5).

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1.1 Social Educational Robotics

There has been a growing interest in using social robots in education [1], in different roles (tutor, peer, tutee), environments (classrooms, lab settings), setups (one or more robots interacting with students individually or in groups) and duration (short to long-term) [2]. Despite this variability, a classification framework (Fig. 2) may be specified using previous definitions of social robots [3–6]. Given this framework, we are defining a standard social educational robot as having the following characteristics, while also presenting a *relaxed* definition specific for this scoping review:

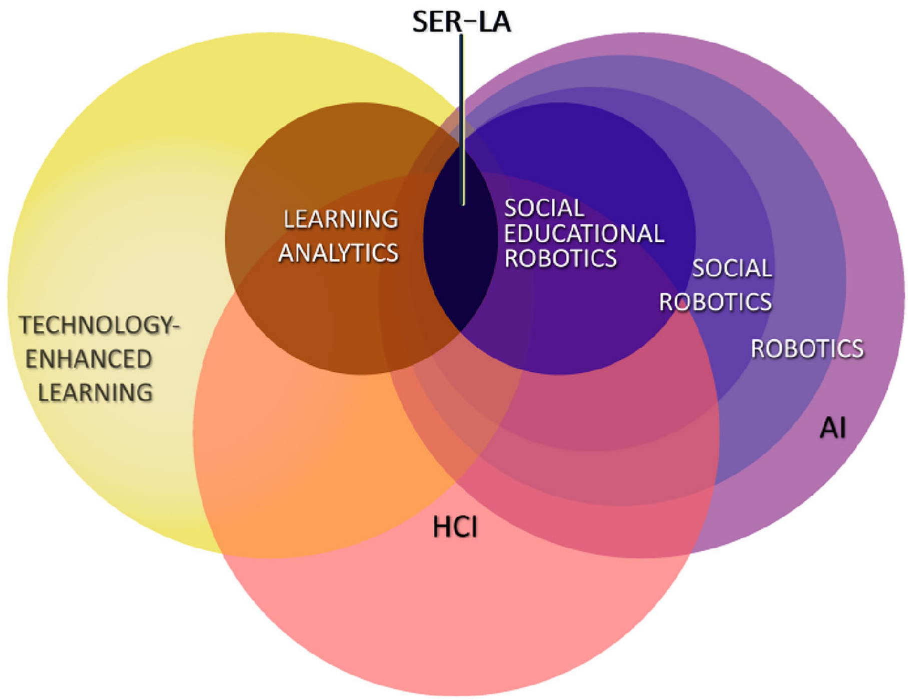

Fig. 1 A conceptual view of the joint research area between Social Educational Robots and Learning Analytics ("SER-LA"). Inspired by [1]

Embodiment. The robot is a tangible artefact [7], equipped with biomorphic features (e.g., eyes, mouth or voice), represented on a screen or physical body, which results in a perception of some personality [4, 5]. *For the scoping review, we relax the definition by not requiring biomorphic features.*

Interactivity. The robot communicates with humans [6] in the same space and time as them, through at least one human-centred interaction modality in both directions [5] and it is capable of playing at least one role with reactions that are — at least in part — a direct consequence of previous actions of the human user [6].

Intelligence. The robot reacts to human actions with non-random behaviour, created with some autonomy [4, 5].

Social norms. The robot is capable of abiding to a common social ground and expectations in interaction with humans [5, 6]. *For the scoping review, we expand the definition by relaxing the need to align with human-like social norms.*

Educational purpose. The robot is able to effectively participate in non-formal, informal or formal educational activities with human students or teachers.

The requirements regarding form and social norms were relaxed to include LA studies in which quasi social robots are used, since they would, within the scope of this review, have been equivalent if a standard social educational robot had been used. It is therefore relevant to include such studies in the review of emerging joint interest.

The relaxed definition includes robots that have an abstract appearance and lack social norms, as long as their functionality allows humans to interact with them in an human-like interaction manner at an adequate level of causality. As illustrated in Fig. 2, the relaxed definition therefore includes the non-biomorphic robot Cellulo, but excludes, e.g., GoGo-Board-based robots, which have too limited and rigid functionalities and arguably no causality in interaction [8]. It should be noted that the markers in Fig. 2 indicate the robots' maximum potential for the corresponding feature and that the actual level in a certain study is dictated by the interaction setting (e.g., restricting the number of modalities used by the robot or its level of autonomy).

1.2 Learning Analytics for Social Educational Robots

LA is classically defined as *"the measurement, collection, analysis and reporting of data about learners and their contexts for purposes of understanding and optimising learning and the environments in which it occurs"* [9]. The distinctive characteristics of this framework (Fig. 3, left), is that it is a **closed cycle** of four steps: (1) Generation of data from a learning environment, (2) Data processing and storage, (3) Analysis of the data and (4) Action to improve the learning environment through prediction, intervention, recommendation, personalisation or reflection [9].

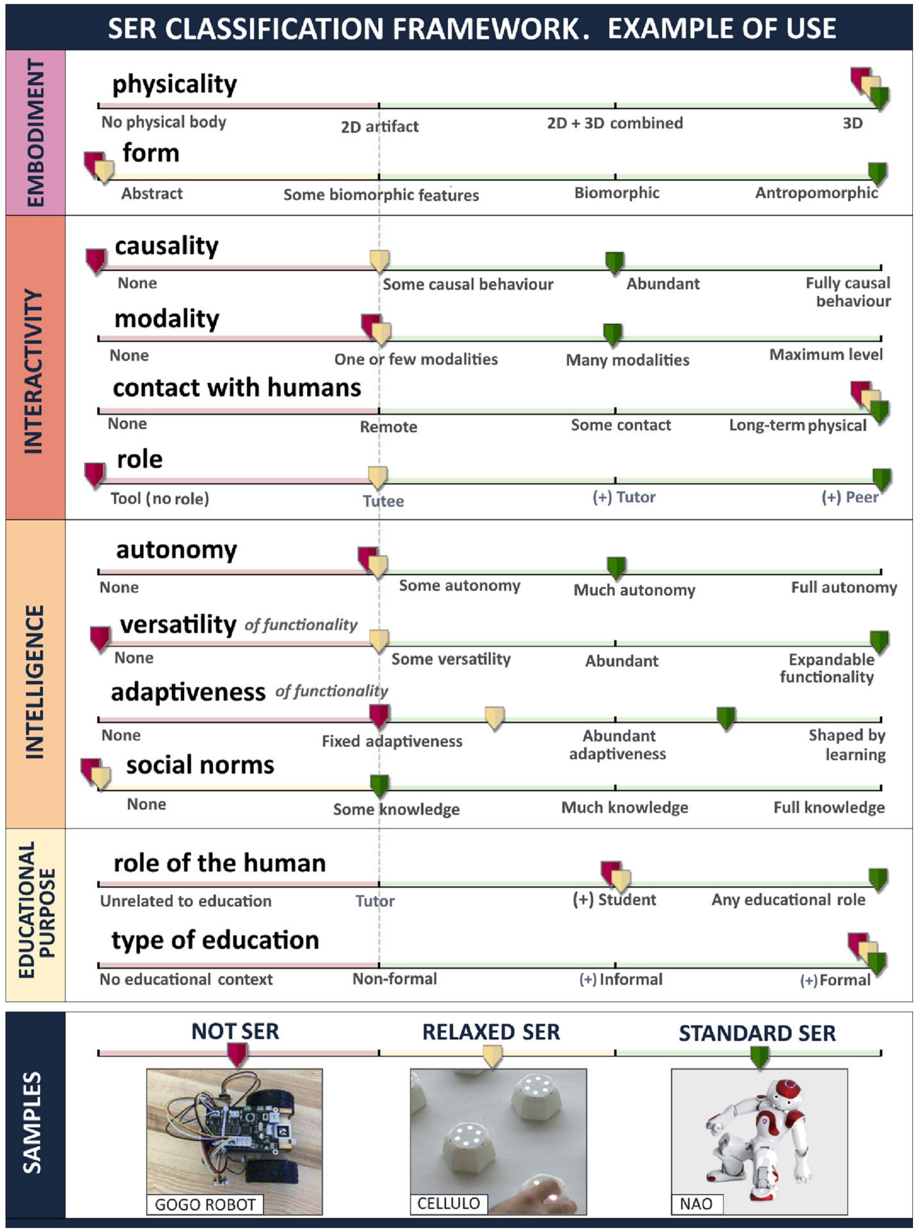

Fig. 2 Classification framework for robots, showing the minimum values for a robot to be considered a SER (vertical dashed line), based on the lowest common level in previous definitions [4–6]. Markers show characteristics of robots included and excluded with the general and the relaxed (for the scoping review) definitions of SER

In its origins, the focus of LA was the study of the actions that students perform while using some sort of digital tool, e.g, learning management systems, intelligent tutoring systems, massive open online courses, educational video games, other computerised systems – or social robots [10].

SER studies may be described by the methodological pattern on the right of Fig. 3. The first three stages are rather similar to the corresponding Learning Analytics cycle, in that a learning environment is created from which data is collected and processed, in order to make interpretations leading to new insights. A main difference compared to the LA cycle is the focus on the human-robot interaction (HRI) as such (the inner HRI cycle in Fig. 3), in which the robot constantly collects data, filters it and interprets it to perform actions within the learning environment. Traditionally, SER studies do not use the collected data to optimise the *same* students' learning, and they do not hence "close the loop" defined in the LA cycle, nor do they normally report back on learning progress to learners and/or educators.

This does not signify that SER researchers are unaware of the potentials of analysing the students' learning. A meta-analysis [2] found that both cognitive objectives (e.g., learning gain, immediate or delayed post-test after exposure to robot, and number of learner attempts) and affective measures (e.g., persistence in terms of attempts made or time spent with robot, number of interactions with the system or emotional expressions of the learner) have been addressed.

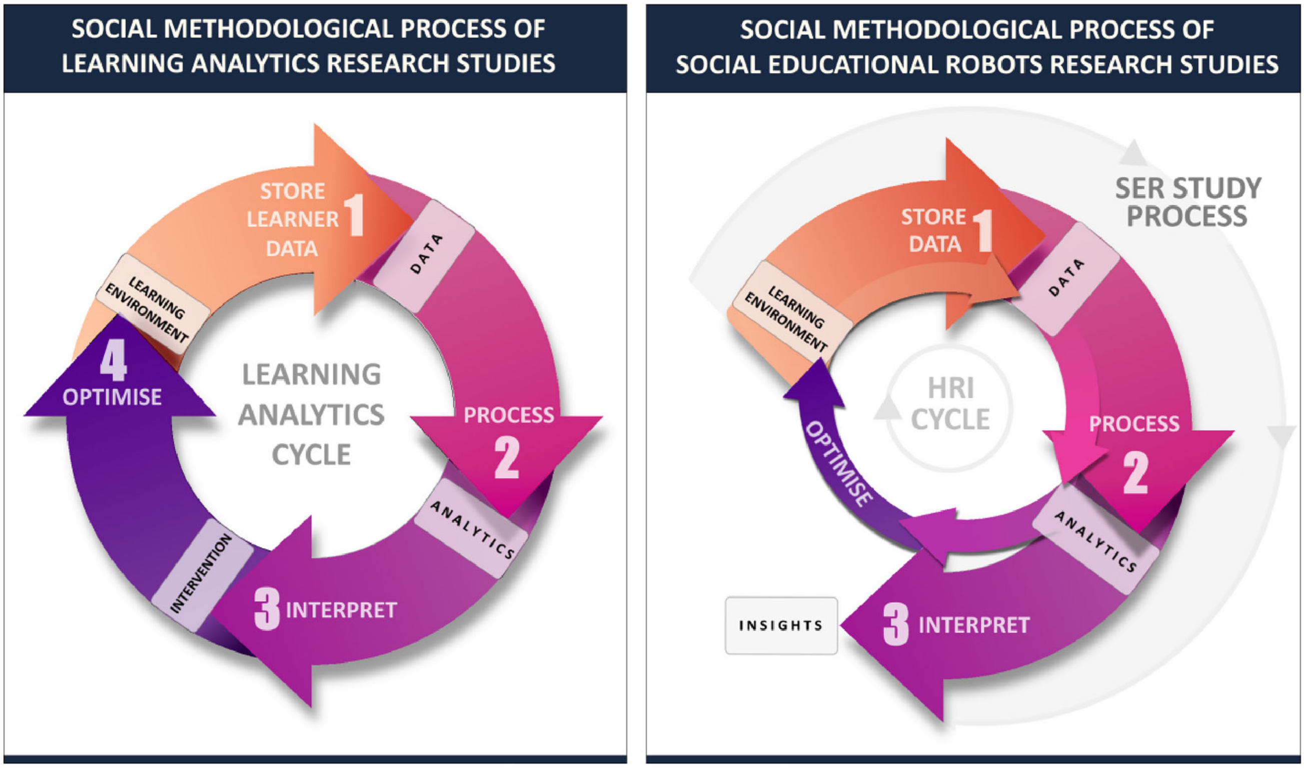

Fig. 3 Methodological processes for Learning Analytics and Social Educational Robotics. The SER process has been schematised to reveal its similarities with the LA, but it is not generally a closed cycle

Such studies may be relevant indications of emerging common grounds between SER and LA, and for the scoping review, we therefore relax also the definition of LA, as follows: LA has not to be explicitly invoked or mentioned and reporting back to stakeholders may be omitted as long as actionable insights aiming to improve learning have been produced from the data and applied to the same learning environment. Reporting to stakeholders is normally essential in LA, but we here take the standpoint that researchers who apply LA unintentionally will likely omit this step, but that it could easily be added, giving a closed LA cycle.

2 Combining Social Educational Robots and LA

SER and LA are currently two of the most active fields within TEL, with a steady growth in the number of publications over the last decade, as shown in Fig. 4. The growth is based on, fundamentally, two reasons [11]. Firstly, the increased research in TEL in general [12], which has spawned interest in more innovative TEL, such as social robots, and has promoted LA as a framework for analysing and evaluating TEL activities. Secondly, the technological progress in both data storage and analytical methods has allowed for improved interaction with social robots (e.g., through better speech recognition and speech synthesis), and for learning analytics on big data.

In particular, interest in multimodality has increased dramatically (the shares of studies including multimodality in combination with LA or social educational robots have more than doubled from 2017 to 2022), as shown in Fig. 4. For LA it has even resulted in an important sub-field, nowadays known as Multi-Modal Learning Analytics (MMLA). This increased interest in multimodal data may lead to mutual interests between LA and SER regarding collection and analysis methods.

From the LA point of view, the need within MMLA to maximise reliability (error-free data collection), validity (data collected of real physical or social properties), diagnosticity (physiological measurements capturing the target construct) and objectivity (adequate procedures in collection, multimodal reduction, analysis and reporting of data to make measures replicable and free of human bias), while minimising intrusiveness [13], should motivate MMLA researchers to use social robots as a less intrusive alternative to collect data, as long as the robot's hardware is comparable to the external collection devices. Social robots further constitute a fundamentally different, and potentially more intuitive, pedagogical intervention approach compared to traditional LA interventions, e.g., learning management systems or massive

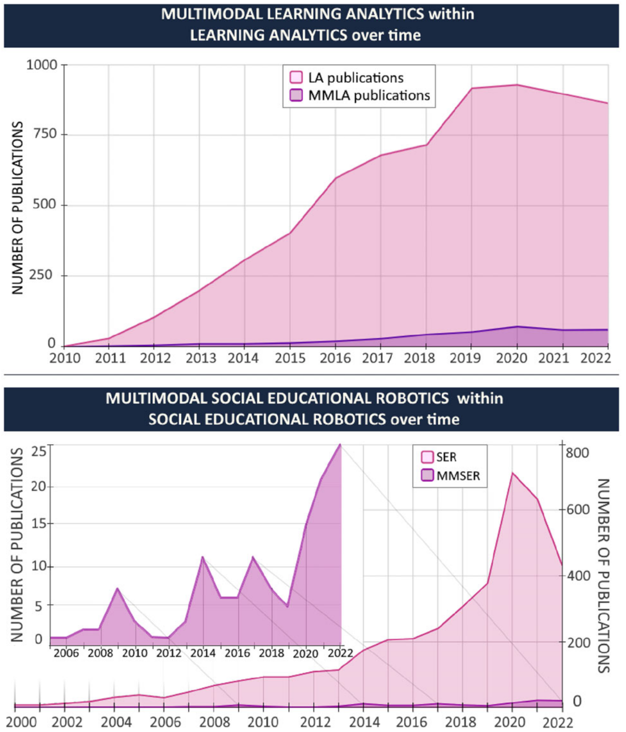

Fig. 4 Number of publications per year in SCOPUS related to (up) Learning Analytics and its subfield Multimodal LA [adding ("*multi-modal**" *OR* "*multimodal**" in the query] and (down) Social Educational Robotics [query: "*social* AND robot* AND (education* OR teach* OR student* OR school)*"] and the sub-field of Multimodal SER, MMSER, [adding "*AND (multimodal* OR multi-modal*)*"]

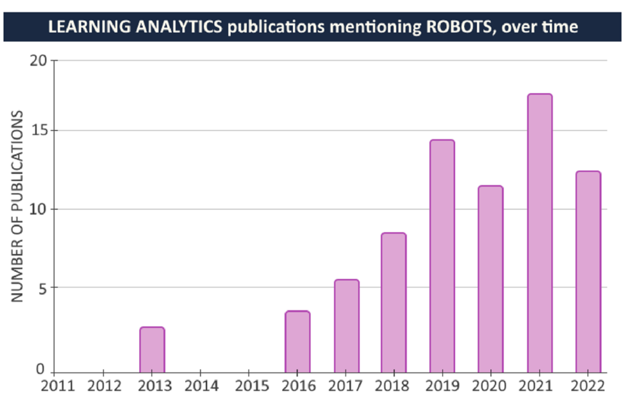

Fig. 5 Number of publications per year in SCOPUS that combine "learning analytics" AND (robot* OR humanoid*)

open online courses, which is one reason that they should be of interest for LA research.

From the social robotics point of view, a systematic review with the aim of providing an overview of research trends, identified Learning Analytics as a relevant research gap [1]. The collection of more advanced multimodal input (e.g., gaze direction, facial and body gestures, and improvements in automatic speech recognition) to analyse the learners' behaviour in the interaction makes the introduction of structured MMLA relevant. However, due to a certain theoretical detachment from the LA field [14], most SER studies have either not completed the LA cycle to achieve a direct, positive intervention on the participating individuals' learning, or, did not refer to this cyclic intervention in terms of LA. This relates both to SER studies related to adaptive learning, where assessment, instruction, learning, and practice are combined to support students [15] and to long-term studies in which the social educational robot was endowed with adaptive behaviour to improve learning. In both cases, collected data is used to optimise the same students' learning, and they do hence "close the loop", but without mentioning LA.

2.1 Is a New Field Emerging?

There are not only theoretical potentials in combining SER and LA, but also a shared fundamental vision that interaction with technology may enhance how we learn and teach [16]. The use of multimodal data increases the common ground and Fig. 5 shows that LA and robots are indeed increasingly mentioned jointly in publications, but a further analysis, as the present survey, is required to determine the extent to which social educational robots or LA are actually *used* in the experiments.

Three types of studies may hence indicate the emergence of a joint research area:

1. studies in which researchers explicitly apply both SER and LA.
2. SER studies in which researchers apply LA without explicitly stating so (or even knowing that they do).
3. LA studies in which researchers make use of robots with some more limited characteristics, but which would have been equivalent if a social robot had been used.

In the last two cases, the convergence of the fields remains unnoticed, as these studies describe the work from the perspective of only one of the research areas. This is the main motivation for carrying out a scoping review that may uncover studies that unknowingly combine SER and LA.

3 The Scoping Review

At a general level, scoping studies *'aim to map rapidly the key concepts underpinning a research area and the main sources and types of evidence available, and can be undertaken as stand-alone projects in their own right, especially where an area is complex or has not been reviewed comprehensively before'* [17]. This definition emphasises both the breadth of what is intended to be explored and its depth, that is, the amount of information extracted and the way in which it will be summarised and reported.

In this study, we attempt to examine the extent, range and nature of research activity combining social educational robots and learning analytics, a research area that has never been reviewed, with the objectives to summarise and disseminate research findings [18] and to identify research gaps, with the overarching aim of informing policy and/or practice [19].

There are a number of limitations of scoping reviews that have been acknowledged, namely an emphasis on breadth of information rather than depth [20] and the lack of appraisal of the quality of evidence in the primary research reports [21], which might result in the loss of relevant publications. Aware of these possible problems, we have taken a few strategic measures (shown in Fig. 6): Firstly, as elaborated in Sects. 1.1–1.2, the definitions of SER and LA have been relaxed in order to detect a larger number of relevant studies. Secondly, more rigorous eligibility criteria have been set to ensure a critical assessment of the included studies. Thirdly, searches have been conducted to refine the search and map different potential sub-fields. The review follows the stages proposed in [21]:

1. Identifying the research question (Sect. 3.1).
2. Identifying relevant studies (Sect. 3.2).
3. Determining study selection (Sect. 3.3).
4. Charting the data (Sect. 3.4).
5. Collating, summarising and reporting the results (Sect. 3.5).

Additionally, we took into consideration both the checklist proposed by Cooper et al. [22] and the PRISMA Scoping Reviews' guidelines [23].

3.1 Identifying the Research Question

The inital research question "*Is Social Educational Robotics and Learning Analytics (SER-LA) emerging as a new field?*" has to be converted into more specific terms, given the vagueness of the terms "emerging" and "new field". We are considering that *self-awareness* is what separates a new field from what its constituent parts were before, namely that researchers are agreeing on a common ground, sharing a set of definitions and methodologies and recognising their own and colleagues' work as of the same type. SER-LA is not at that stage yet, but we postulate that it might be in a preceding stage, which means that some of the indicators would be different. Section 2 (synthesised with points 1–13 of Fig. 6) explored this postulate, analysing what possible directions the trend could be heading in and what the possible motivations could be. This analysis not only provided the basis for the search for SER-LA studies (points 14–18), but also helps to define the sub-questions that will be answered in Sect. 4, based on the scoping review:

1. How have studies in the field emerged over time?
2. Do the identified studies display awareness of both SER and LA?
3. Direction of the emergence; i.e., is it mainly LA studies that start to make use of social educational robots, or is SER research starting to include LA?

The last question may be investigated by exploring to what extent increased multi-modality in LA data collection, on the one hand, and long-term SER studies on robot adaptivity, on the other hand, are driving forces towards a joint field.

3.2 Identifying Relevant Studies

The literature search was performed within the following six search databases: Scopus, Web of Science, Science Direct, EBSCOhost, ACM Digital Library and Wiley Online Library. This choice was made to ensure a good coverage within the Technology-Enhanced Learning field and to allow for adequate complexity of the search strings.

The search strategy is summarised in Fig. 6, in which we highlight the underlying trends for the two fields (points 1–4), the researchers in the two fields (points 5–9) and the need for a specified definition of SER and LA (points 12–13). Two sets of searches were performed: one (henceforth denoted as SEARCH-1) of publications in which the terms "Learning Analytics" and "[Social] robotics" were explicit (points 14, 15, 17) and a second one (henceforth SEARCH-2) in which the term "Learning Analytics" could be missing, but terms related to adaptiveness, learning personalisation, long-term and education were included (points 16, 18).

We restricted the baseline search to the time span between January 2011 and December 2022. The start date was selected as 2011 since this is deemed to be the year when LA was born [24]; and a search for terms "Learning Analytics" in SCOPUS returns no results before this year (Fig. 4). The two searches produced a total of 682 and 673 results respectively, as detailed in Fig. 7. Additionally, we identified a number of further references from the bibliographies of relevant studies found through SEARCH-1 and SEARCH-2 (nine and twenty, respectively), as schematised in the top section of Fig. 7.

3.3 Study Selection

This stage was particularly important in that inclusion/exclusion criteria would have a direct impact on the results, and therefore on any conclusions later drawn. We proceeded as detailed in Fig. 7, starting from the Screening layer.

We utilised the software JabRef to store all 1384 records and filter out duplicates. 1056 records were then exported into CSV format. With a series of formulas, we incorporated a ranking mechanism whereby each publication was given a score depending on how many key terms related to

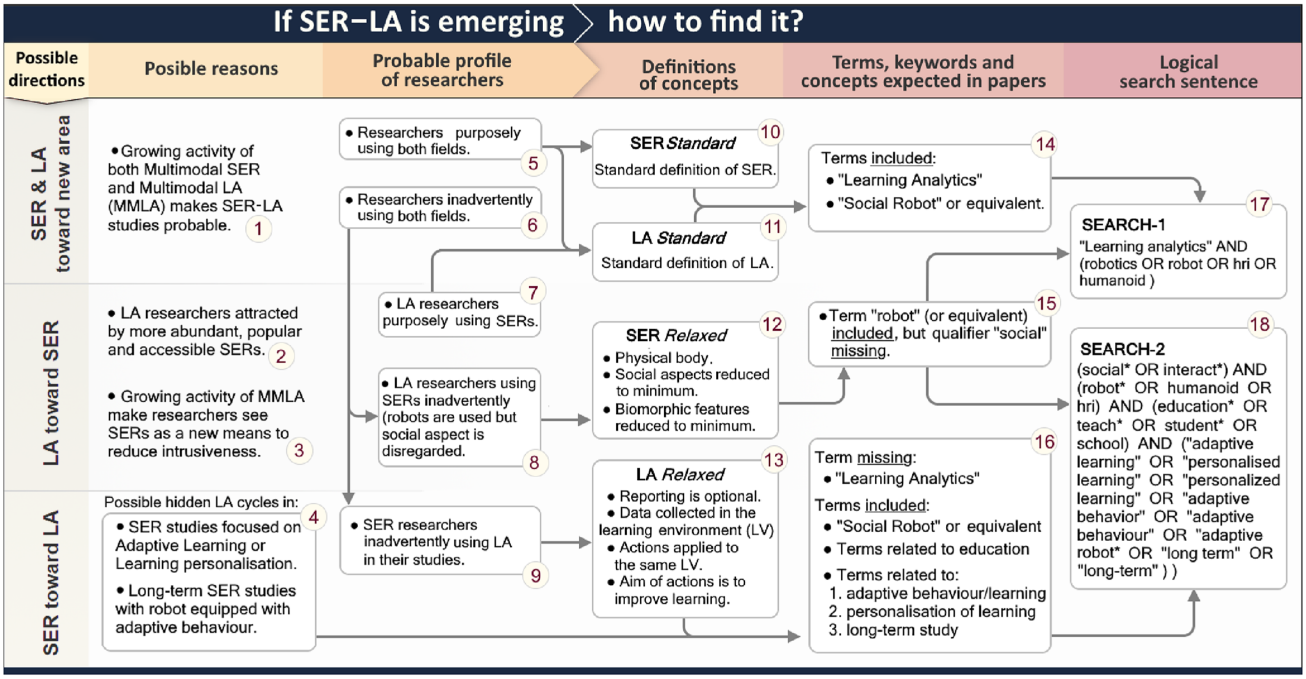

Fig. 6 The rationale behind this study's analysis of the SER-LA research field, combined with the design of search sentences used in the scoping review. Numbers indicate the different steps of the study that are referred to in the text

LA and SER were found in the title, the keywords and the abstract, and the number of occurrences. The latter was not utilised to accept studies, but to assist the screening process and help reject those with too low score. Next, we discarded studies mistakenly included by the search engine (e.g., too old publications or not written in English), proceeding prefaces and editorials. These correspond to the first three eligibility/rejection criteria listed in Fig. 7 (centre frame in the middle).

The next step of the screening consisted mainly in perusing study title and abstract to discard studies that were not related to education (eligibility criteria 4–6), excluding studies "*about* robotics, not *with* robots". At this point of the screening, 272 studies were selected for further inspection.

In the last step, all 272 articles identified were read in full and assessed according to the eligibility/rejection criteria listed in Fig. 7. We were particularly careful with the inspection of the last two criteria. *"Not about learning"* means that studies were excluded if the aim of the investigation was not to improve the learning process. Examples of this are two studies [25, 26] focused on the constructed Robot Interaction Language (ROILA). Although data was collected and employed to influence the interactions, the studies were excluded, since the aim was not strictly to improve the learning process, but rather to study participants' cognitive capacities. *"Learning Analytics cycle"*, on the other hand, signifies that SER studies were included if the robot had an adaptive behaviour aiming to create some personalised learning, thus creating a form of LA cycle: (1) learning environment data collected, (2) processed and analysed, and (3) interpreted aiming to (4) updating the robot's behaviour in the learning setting; establishing, in fact, the beginning of a new cycle. However, we required that the adaptive behaviour of the robot was based on data captured *during* the interaction. Consequently, we rejected those cases in which personalisation was achieved on the basis of prior information (e.g., demographics information or pre-test assessments).

This last screening process resulted in 243 articles being excluded, ending up with 29 identified studies that will be discussed in further detail in the following sections.

3.4 Charting the Data

Since scoping studies aim to present an overview of all material reviewed (prioritising breadth over depth), a large body of material may need to be presented. However, since our review resulted in a relatively low number of studies, we will describe them in some more detail.

The charting was initially guided by the four phases of the Learning Analytics cycle (Fig. 3). Iteratively, additional features were identified and (re)organised, resulting in the list of 22 characteristics shown in Fig. 8.

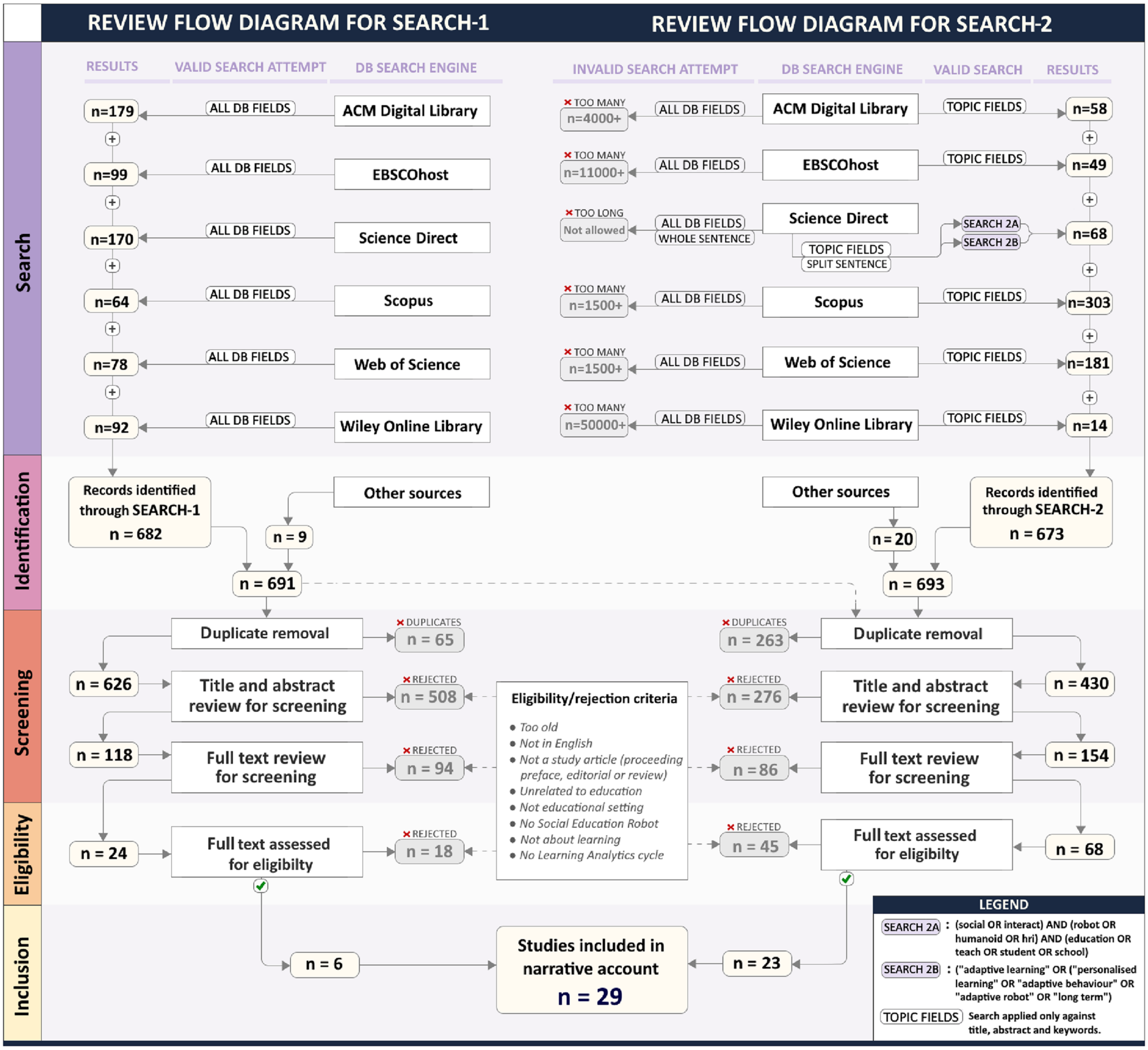

Fig. 7 Scoping review flow diagram. SEARCH-1 and SEARCH-2 are shown in Fig. 6, points 17 and 18 respectively

3.5 Collating, Summarising and Reporting the Results

The studies are presented firstly according to the phases of the LA cycle and secondly regarding the learning outcomes that were the objective of the studies.

3.5.1 The Phases of LA Cycle

We here summarise the different common aspects of the studies, with the exact numbers related to these common aspects are provided in Fig. 8. The identified studies focused on mostly minor students (n=26) in settings corresponding to formal education (mainly in elementary school and middle school). The eight remaining cases were non-formal education settings, with three cases established as part of therapy programs (centred on disease management [27], on handwriting for students with visuoconstructive deficits [28], and on maths for ASD infants [29]). Another three cases [30–32]) invited preschool and elementary school learners to participate in ad-hoc learning activities (second language, collaborative task and maths, respectively) that were unconnected to their academic curriculum. Finally, two other studies [33, 34]) targeted adult learners for mathematics activities.

The learning environments were mainly of lab-type and STEM subjects dominated over non-STEM topics. The three non-curricular subjects corresponded to handwriting prac-

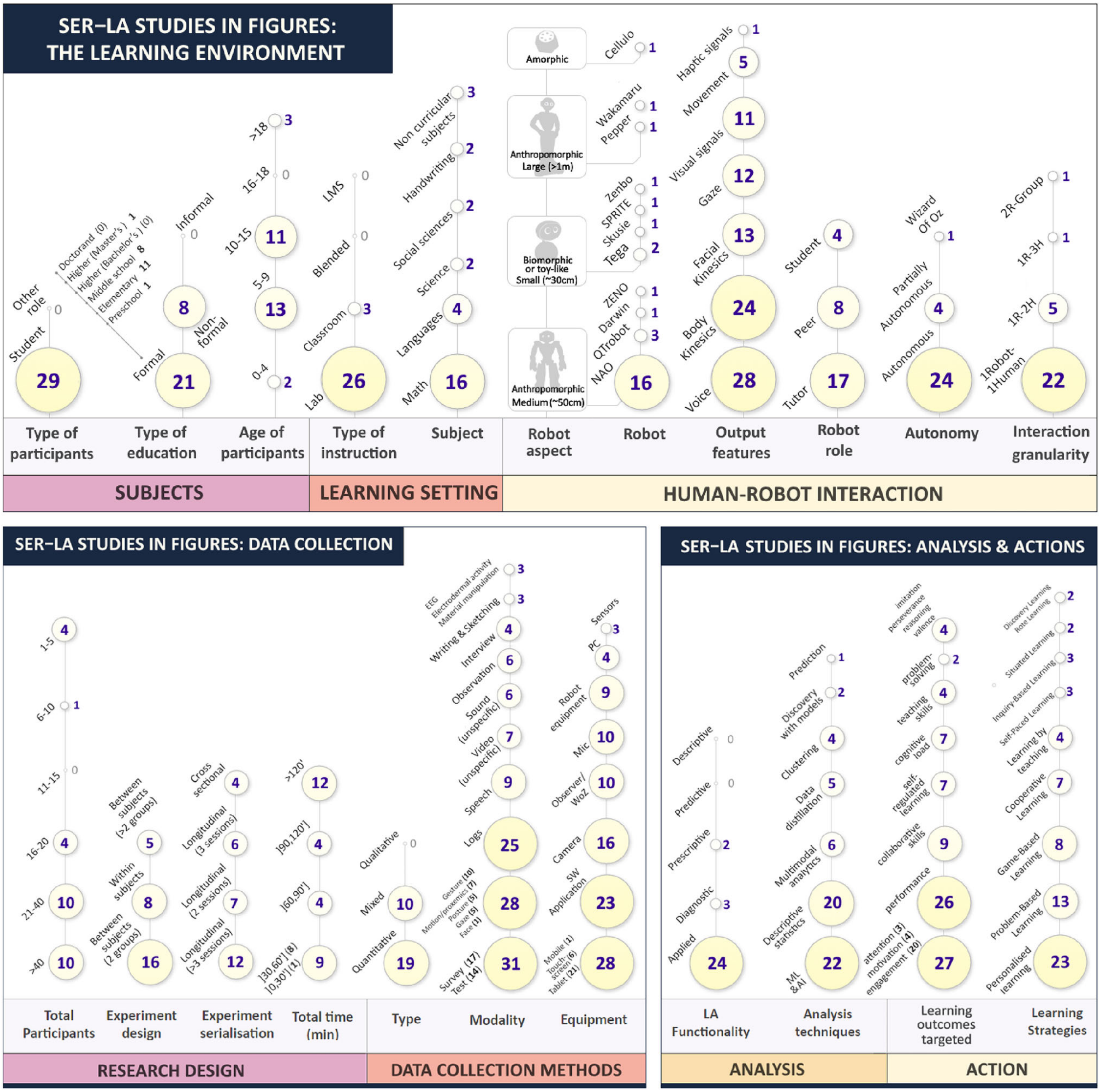

Fig. 8 Summary of the properties of the reviewed articles for the most important characteristics related to the four phases of the Learning Analytics cycle

tice, storytelling comprehension and game activity to foster collaborative learning.

With regards to how HRI characterised the studies, the majority of the robots chosen were similar in terms of interactivity and intelligence: potentially with high levels of autonomy and number of input and output modalities. In terms of embodiment, we observe the four main types shown in Fig. 8, used with learners of partly different ages. The most frequent option (n=21) corresponds to anthropomorphic robots with a height of around 50 cm and includes NAO, QTrobot, Darwin and Zeno R25. The participants in these studies covered all age ranges, but were mainly between 5 and 15 years old. The second type of robot is smaller (around 30 cm) and has a toy-like appearance and fewer anthropomorphic features (Tega, Skusie, Sprite and Zenbo); incorporating more vivid colours and neotenic characteristics. The Tega, Skusie and Sprite robots were used in five cases with participants younger than 10 years old and two Zenbo robots were used in one study with high-school students in classroom setting [35]. The third type of robot (represented by Wakamaru and Pepper) is similar to the first, but is larger (at least 100 cm tall) and was used in two studies with adult learners. The last type is the small amorphic robot Cellulo (shown in Fig. 2, bottom) that qualifies for the review with the relaxed definition of SER.

The role played by the robot is also to some extent coupled with the age of the students. The robot acted as a tutor (alternatively described as "guide", "instructor" or "mediator") in eleven of the seventeen studies in which the students were ten years old or over, whereas it acted as a "peer" or as a "student" in nine out of the twelve studies in which the students were ten years old or younger.

In total, the robots interacted utilising 94 output modalities (μ=3.24; σ=0.87), with a minimum of two modalities (eight cases) and a maximum of four (15 cases). The most chosen modalities were voice and body kinesics, followed by either face kinesics, gaze or visual signals.

Regarding the granularity of the interaction, the most common setup was the dyad (one robot and one student), which, on average, had 27.7 participants (σ=15.6). The remaining seven studies used one robot and two or three students or two robots and a group and had an average of 40.4 participants (σ=18.1).

For the second phase of the LA cycle (data collection), Fig. 8 offers a compilation of characteristics organised in two categories: research design and the methods utilised to collect the data. Regarding the first aspect, the most common research design (n=25) was longitudinal (serialised in two or more sessions), that were at least one hour long, and used a between-subject strategy (n=21). The rest of the cases were cross-sectional, less than one hour long, and either used within- (n=2) or between-subject (n=2) strategies.

All 29 investigations used quantitative data collection methods (ten of them partially), totalling 122 input modalities (μ=4.2; σ=2.1), with a minimum of two modalities [34, 36–38] and a maximum of nine [32]. It is worth making the distinction between, on the one hand, the 50 instances in which input modalities that could potentially be collected by robots (sound, video and recognition of human motion, posture, gesture, gaze, face and speech) were used and, on the other hand, the use of external data collection methods (observation, interviews, surveys, exams, logs, writing/sketching recognition and other sensors, such as electroencephalography (EEG), electrodermal activity and object manipulation). As will be discussed further in Sect. 4, only four studies did in fact collect audiovisual data with the robot in at least one modality (n=4 [32], n=3 [27, 39], and n=1 [35]). In addition, haptic input was collected in one study [37]. All studies employed an external device for at least one modality: specific software application installed on touchscreen devices (e.g., multitouch tables, tablets and mobiles) and computers, cameras, microphones and sensors (devices for capturing EEG, electrodermal activity and research material manipulation).

3.5.2 Learning Outcomes Targeted

For the learning outcomes, we distinguished between *instructor-centred* and *learner-centred* outcomes, which are further associated with the different learning domains. To do this, we propose a classification of learning domains consisting of five categories (cognitive, affective, social, psychomotor and metacognitive), inspired by Bloom's taxonomy [40] and the so-called "Learning Power" framework, by Claxton [41]. We identified the learning outcomes of each study, as summarised in Fig. 8 (right), identifying learning outcomes in all of the learning domains, with the exception of the psychomotor domain, and finding that Performance and Engagement dominated as learning outcomes. At learning domain level, the cognitive domain was the most targeted, with 36 occasions (summing over Performance, Cognitive load, Problem-solving and Reasoning), followed by the affective domain, with 28 occasions (summing over Engagement, Motivation, Attention and Perseverance). Social-domain learning outcomes were main objectives in 15 studies (summing over Collaborative skills, Teaching skills, Imitation and Valence). Finally, the metacognitive domain (Self-regulated learning) was targeted seven times.

4 Discussion

At this stage, we put in perspective, relate and discuss the results using the different sub-questions in Sect. 3.1 as structure and Fig. 9 to give an overview.

4.1 Emergence Over Time

We found it most relevant to focus on the distribution over time of the 29 identified studies, as this may give an indication of if the interest in the field is increasing. Figure 9, in its central section, shows the studies in chronological order. Most studies (n=23) were published in the last five years, with seventeen in the last three and only three studies prior to 2016. This is hence consistent with the expectations that the field has emerged recently and is expanding. It is important to remember that this happens despite the COVID-19 pandemic in the early 2020 s that drastically reduced the number of user studies, particularly in the field of social robotics (Fig. 4).

Special attention should be paid to the five studies that explicitly state that they combined social educational robots and LA [31, 35, 42–44], which were all published between 2020 and 2022, whereas most of the other studies (n=23) occurred before 2020. This supports the hypothesis that a

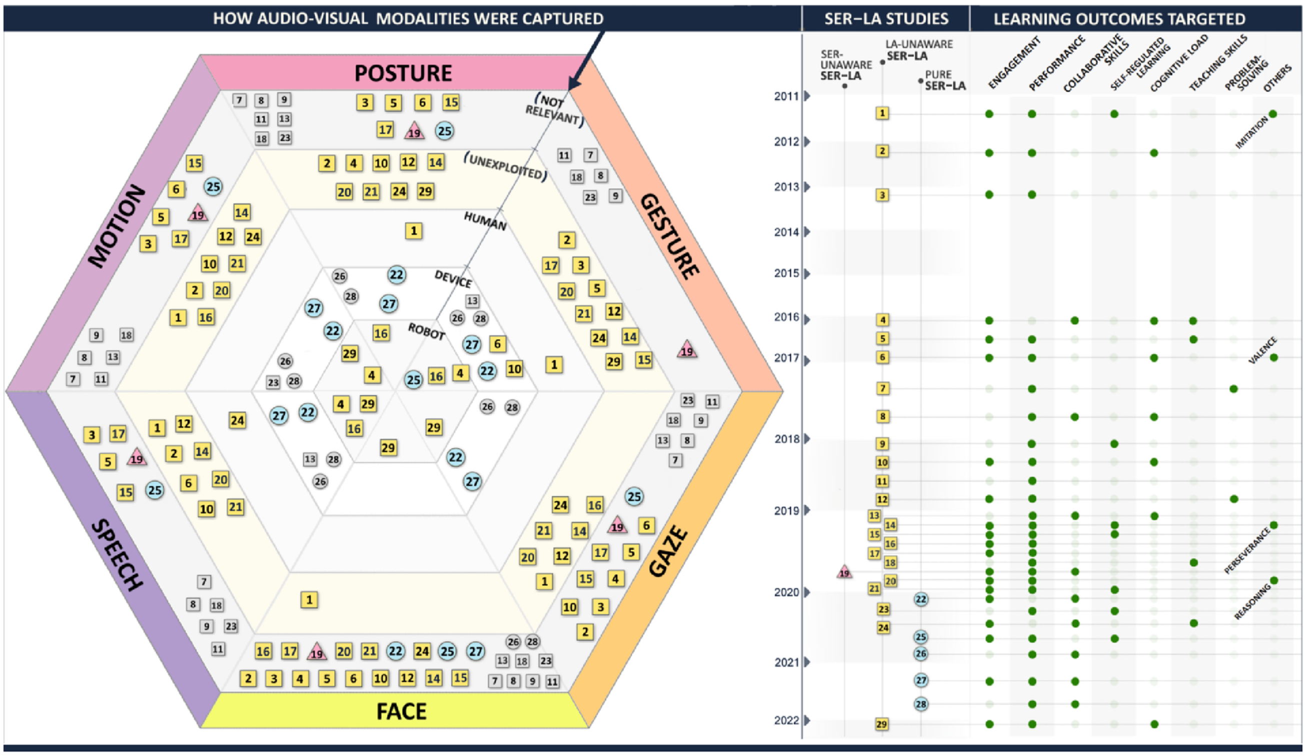

Fig. 9 Per-study overview of the reviewed studies. **Left:** the hexagon edges show the six most common input modalities social educational robots are typically equipped with (*face* refers to face recognition of an individual whereas *gesture* applies to facial expression recognition, including emotion recognition and body posture). The inner canvas of the hexagon is composed by five layers corresponding to possible types of data-collectors: from centre and outwards: a robot, a device and a human. The outermost "Not relevant" layer indicates that the modality was not collected in the study nor would it have been possible, whereas the yellow "Unexploited" layer refers to modalities not collected in the study, but that would have been relevant and possible to collect with the robot. Icons for the 29 studies are arranged on the canvas according to how data was collected for each modality (by robot, by device, by human, exploitable, or irrelevant). The icons of the studies that aimed at "engagement" as a learning outcome are shown in colour, while the others are shown in gray. The shape and colour of the symbols relate to awareness of the two fields (as shown in the sorting under the heading SER-LA STUDIES in the middle pane). **Middle:** Studies presented in chronological order and classified according to discipline awareness. **Right:** Learning outcomes targeted to improve learning

joint research area is developing, since investigations that *purposely* contributes to both fields should be expected to occur after a number of inadvertent contributions have been made.

4.2 Awareness of SER and LA

In Sect. 2 we highlighted that both LA and SER scientists may be contributing to the field *inadvertently*, due to lack of knowledge of the other discipline, as also summarised in points 8 and 9 of Fig. 6. Thus, we classify the studies into LA-unaware, SER-unaware and pure SER-LA:

- **SER-unaware** refers to studies in which LA scientists used robots that are included according to the relaxed definition of SER. We found one such case [37], denoted with △ in Fig. 9, which used the Cellulo robot.
- **LA-unaware** refers to studies in which SER researchers did apply some form of Learning Analytics in their work but without mentioning it. We found 23 such works, shown with squares in Fig. 9: $\boxed{1}$ [45], $\boxed{2}$ [46], $\boxed{3}$ [33], $\boxed{4}$ [27], $\boxed{5}$ [28], $\boxed{6}$ [47], $\boxed{7}$ [48], $\boxed{8}$ [49], $\boxed{9}$ [50], $\boxed{10}$ [51], $\boxed{11}$ [52], $\boxed{12}$ [34], $\boxed{13}$ [53], $\boxed{14}$ [54], $\boxed{15}$ [36], $\boxed{16}$ [39], $\boxed{17}$ [55], $\boxed{18}$ [56], $\boxed{20}$ [29], $\boxed{21}$ [30], $\boxed{23}$ [57], $\boxed{24}$ [38], $\boxed{29}$ [32].
- **Pure SER-LA** studies are investigations that explicitly combine SER and LA. The five such studies are marked with circles in Fig. 9: ㉒ [31], ㉕ [35], ㉖ [42], ㉘ [43], ㉗ [44].

Regarding LA researchers' awareness of the benefits of social educational robots, it is worth noting that several LA studies were excluded during the screening stage derived from SEARCH-1, as they used other types of robots. In many of these cases, however, the studies could have been conducted with social educational robots after minor changes. Two examples are the GoGo-Board-based robot, which has too limited and rigid functionalities and arguably no personality [8] and the "Materials Recovery Facility" [58], which was capable of interacting with humans around a learning activity, but only as a tool.

The above may constitute an indication of LA researchers' lack of awareness about the advantages of social educational robots, especially in Multimodal Learning Analytics studies. This underutilisation of social educational robots within LA may explain why the surge of LA studies using robots in recent years (Fig. 5) does not seem to have massively materialised in use of social educational robots.

Regarding SER researchers awareness of LA, 23 out of the 29 studies (all derived from SEARCH-2) were defined as LA-unaware, showing (1) an increase in the study of adaptive behaviour and learning of social robots in educational settings, (2) a very probable lack of awareness by SER researchers regarding how related to LA their work actually is and (3) that direct contributions to LA research pass unnoticed by the LA community.

4.3 Direction of the Emergence

For the third sub-question, we turn our attention to evidence suggesting, respectively, that LA studies start using social educational robots and that SER studies start using MMLA.

LA studies using social educational robots have increased in the last five years (Fig. 5) and this was one of motivations for this review. The scoping review found six studies which *deliberately* combined LA and social robots (one case of SER-unaware LA [37]; and the five pure SER-LA [31, 35, 42–44]), all six published 2019–2022. It is also relevant to mention nine LA publications between 2018 and 2022 that used other types of robots [8, 58–65], adding evidence for an emerging area. This is further supported by a recent study [66], which would have been included as a pure and highly multimodal SER-LA study in the review had it been published at the time of the database searchers. The study explored 25 multimodal features, collected using eye tracking, video and infrared cameras, human annotation and self-assessment, to study how the social robot Furhat could support students' attention in e-reading, using machine learning attention prediction based on a large multimodal dataset. The facts that this study is published in the major international LA conference (Learning Analytics and Knowledge, LAK), that it collects extensive multimodal data (albeit not with the robot) and that it explores machine learning MMLA are clear indications that social educational robots are becoming an influential intervention method within LA.

Multimodal data was central for all the 29 studies, which is a key characteristics, since multimodality within LA and SER *separately* is still only used in a small, albeit increasing, fraction of the studies (cf. Figure 4). This focus on multimodal data could potentially encourage LA researchers to employ social robots as data collector. Since promoting learners' *engagement* was the targeted outcome in 20 of the studies and since engagement can, to a certain degree, be determined from gestures, body language [67], motion and proxemics [37] and speech and gaze [68], we focused on what modalities were used for data collection in these studies and how the data was collected (by a robot, a separate device or a human). We then analysed how this matches the typical audiovisual input modalities of social educational robots (motion, posture, gesture, gaze, face and speech) and whether the data *could have been* collected by the robot itself. To exclude cases when the robot could not collect the data, a number of factors were considered for each modality: *Hardware* (e.g., Cellulo [37] does not possess sufficient capabilities to capture any of these modalities), *Setting* (e.g., too large distance between robot and student hinders gaze detection, as in [27, 46]), and *Procedure* (e.g., speech recognition has no value if students are not expected to speak during the interaction, as in [28, 36, 55]).

The coloured icons in the three inner-most hexagons in Fig. 9 offer a visual representation of the data collection in the 20 engagement studies, showing large differences between different modalities. *Gesture* was collected in eight studies (four by a device, three by a robot, one by a human), it could have been collected by the robot in 11 other studies, and gesture data collection was impossible in only one case [37]. *Face recognition*, on the other hand, was not collected nor could have been collected by the robot in 18 studies (ten due to *Procedure*, five due to *Setting* and one due to *Hardware*). For the rest of the modalities, they were, or could have been, collected by the robot to similar degrees: *speech* (n=6+8) *posture* (n=4+9), *motion* (n=4+9) and *gaze* (n=3+7).

In summary, out of a potential maximum of 120 data collections (six modalities and 20 studies), 26 modality collections occurred. Our analysis assessed that data collection in the modality was irrelevant or unfeasible 49 times (shown as Not Relevant), but that data from the modalities could have been captured with the robot an additional 45 times (shown as Unexploited). There is hence a number of unexploited modalities in the experiments and, with the trend to collect data from more and more modalities, this could be a push in the direction of combining MMLA and social educational robots. Indeed, the six pure SER-LA studies employed substantially more input modalities on average (μ=6.33; σ=2.42) than the 23 LA-unaware studies (μ=3.65; σ=1.58) and used multimodal data analytics [69] to explore the data.

SER studies using LA explicitly were not found, but a strong indicator of a LA becoming relevant within SER is that the main contributors to four [31, 42–44] of the five pure SER-LA studies have mainly been active in the field of social educational robotics, but have *also* been consistently contributing to Learning Analytics in recent years. In addition, the 23 studies focused on social educational robots that did not state that LA was being applied, focused on robot adaptiveness and long-term designs, which has nevertheless approached them towards the LA field.

Robot adaptiveness may, as explained in Sect. 1.2, contribute to closing the full LA cycle for SER studies. All 23 LA-unaware investigations employed robots that adapted to students' learning. For example, personalising the feedback to the attention or the performance [33, 36, 45, 48, 51]; adapting the instruction [27, 49, 55]; personalising immediacy cues depending on student's engagement [46, 47]; or adjusting performance to the student's teaching skills [28, 38]. As for the research design, 22 studies employed a serialised implementation (21 longitudinal-design experiments extended over multiple sessions and one cross-sectional experiment with a single session serialised in four episodes [48]). Only one investigation was implemented in a single non-serialised session [46].

A deeper analysis of these data suggests that the determining factor for how adaptive behaviours of the robots is designed is how frequently the system can update its behaviour based on learner data. In particular, this relates to the choice of data (e.g., EEG activity, knowledge-level of the learner) and what discretisation is possible (e.g., EEG activity markers per unit of time has a higher update rate than number of correct learner answers). This can be illustrated by two contrasting examples.

In the first study [54], an adaptive robot tutor supported the learning process of students when they solved mathematical problems. Three dimensions – levels of knowledge and commitment, and number of attempts at mathematical problems – were measured over five sessions during two weeks. The serialisation and the longer duration were required partly because the variables (e.g., attempts at a maths problem or answers to online survey Likert-scale questions) and the frequency with which the robot could adapt to these was low and irregular.

In the second study [46], an adaptive robot monitored student attention in real time using measurements from EEG and, in turn, recaptured diminishing attention levels using verbal and nonverbal questions. The session required no more than 30 min to capture data, analyse it, feed the adaptive-behaviour policy of the robot and influence learning positively. This was in part possible since the data (EEG activity) was collected with high frequency and the adaptive behaviour of the robot could hence be updated more quickly.

Thus, we found that adaptive robot behaviour is conducive to the full LA cycle taking place, but that the necessity to update the behaviour with sufficiently meaningful input data may result in serialisation or long-term designs. This low update frequency of the LA cycle, may hinder SER researchers to be aware of the similarities with LA methodology.

5 Conclusions

This review has revealed that the research activity on the border between SER and LA has increased dramatically in the last five years from the very low activity of the previous seven. Rather than trying to conclude if this proves that a new sub-field is in fact forming, it is more worthwhile to observe that the convergence of the two fields has been shown to be not only empirically valid but also fruitful for future use in certain educational contexts.

Social Educational Robots have long been promoted as a natural part of future digitised education, similarly to how today much technological equipment (e.g., electronic whiteboards, smart screens, tablets) is commonly used in classrooms, without any of the "novelty effects" they used to cause. Recent technical progress has favoured combining SER and LA (social educational robots have become more diverse, powerful and versatile; and MMLA has benefited from new computational analysis techniques from data science and Artificial Intelligence [13]) and we found two inspiring real-world use cases for educational robots and LA among the studies in this review, which illustrates how social robots and LA could be combined in actual education.

The first use case consists of incorporating social educational robots as teaching assistants in classrooms, as exemplified by placing two Zenbo robots placed at the front of a secondary school classroom [35]. With this setting, the robots complement the teacher-led instruction, act as an incentive for student engagement and can, at the same time, collect information on class dynamics at group level.

The second use case consists of giving the social educational robot a supporting role in dyadic student-student interactions with the robot as a by-stander, as already explored in elementary [31] and secondary school [42–44]. In this use case, the social robot provides feedback and/or motivation for students on demand or as required, while collecting data about students' learning and interaction at both dyadic and individual level.

We argue that both these application scenarios are ideal for Learning Analytics, for a number of reasons. Firstly, social educational robots have much unexploited potential as potent and unobtrusive multimodal data collectors, as outlined in Sect. 2.1. Secondly, social educational robots are equipped with the capacity to connect to other devices (i.e., computers, tablets or mobiles) or applications (i.e., LMS, Tutoring Systems), which are well-established tools in LA interventions. We observed two examples of this possibility [28, 33], in which social educational robots exchange data with tablets and educational applications via Bluetooth. Thirdly, social educational robots are themselves interactive agents capable of communicating and, therefore, fulfilling the LA task of reporting to students or teachers, either on request or driven by events during the interaction. Examples in this review

[31, 33, 36, 42–44, 51, 55] showcase how social educational robots adapt the feedback provided to the students based on various factors processed in real time. Fourthly, both application scenarios establish stable conditions over long periods of time, which favours the study and analysis of the complex dynamics of the teaching-learning process. Many LA techniques (e.g., Social Network Analysis, Process mining) gain effectiveness when applied to a large amount of serialised data over long periods [70].

To conclude, we would like to offer researchers from both disciplines some recommendations to advance the joint field: *LA scientists* may need to reevaluate their understanding of social educational robots. Rather than just another teaching strategy or tool for temporary use, at the level of many others, social educational robots can be seen as a sophisticated version of a tutoring system that is at the same time capable of simultaneously collecting abundant multimodal educational data unobtrusively and providing sustained, personalised, and interactive real-time feedback. *SER researchers* are encouraged to reflect on the possibilities of improving the students' learning based on the findings of their studies, i.e., shifting the goal from completing a research study on social robots to providing actual students with a valuable learning experience. This is especially true for studies conducted in formal educational settings, since, in many of them, conveying or applying new insights is all that is required to *close the LA loop* and intervene positively in the learning process of the learners of the study. This would be an important starting step to integrate LA in SER research and thus contribute directly to both fields.

Researchers from both disciplines are encouraged to form multi-disciplinary collaboration to improve digitised education by exploring how social robots and LA may be combined in new application settings. Both fields actually have the motive, means and opportunities to make this happen.

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