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The Interplay of Learning Analytics and Artificial Intelligence

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***Abstract*—The widespread use of digital systems and tools in education has opened up opportunities for collecting, measuring, and analysing data about user (learner, teacher) interactions with a variety of learning resources and activities, with the ultimate objective of better understanding learning and advancing both learning outcomes and the overall learning experience. This promise motivated the development of Learning Analytics (LA) as a research and practical field and the use of insights derived from learning trace data for evidence-based decision making in a variety of educational settings. While LA has made a significant contribution to better understanding of learning and the environments in which it takes place, many open questions and challenges remain. Furthermore, new opportunities and challenges continue to emerge with the ever-changing modalities of teaching and learning, the latest of which are associated with the rapid development and accessibility of Artificial Intelligence (AI). Taking the cyclical model of LA as its exploration framework, this paper examines how key components of the LA model – namely data, methods, and actions – relate to and may benefit from the latest developments in AI, and especially Generative AI. Aiming for evidence-based analysis and discussion of the interplay between LA and AI, the paper relies on the latest empirical research in LA and the related research fields of AI in Education and Educational Data Mining.**

***Index Terms*—Learning Analytics, Artificial Intelligence in Education, Generative AI.**

I. Introduction

THE educational landscape is undergoing a continuous digital transformation. Online and blended learning modalities are flourishing, and a vast array of software tools and gadgets are now commonplace in classrooms. These advancements allow for the unobtrusive gathering of data about learners' interactions with learning resources and other participants in the educational process. This wealth of data provides a rich foundation for understanding learning and advancing learning outcomes and the overall educational experience. Different approaches have emerged to achieve these objectives, ranging from fully automated systems aimed at personalising learning according to individual learners' needs and preferences to those that provide learners with information—such as analytics, recommendations, and pedagogical scaffolds—empowering them to take initiative and adapt their learning pathways on their own. This paper focuses on the latter group of approaches, which emphasise user agency and adaptable learning processes and are central to the field of Learning Analytics (LA).

The recent rapid advancements and adoption of Artificial Intelligence (AI) has opened new opportunities and challenges in educational settings. Generative AI, with its advanced capabilities, promises to significantly impact how educational content is created, delivered, and used. The field of LA, with its established methodologies for studying learning, is well-positioned to systematically explore and understand the benefits and drawbacks of incorporating (Generative) AI into education.

Set against this backdrop, this paper aims to achieve two objectives. First, it introduces LA, highlighting its iterative nature and the key elements of the LA process. Second, it explores the interplay between LA and AI, by focusing on how LA can enhance our understanding of AI in education and how the LA process and its key components may benefit from advancements in (Generative) AI. By examining these dynamics, the paper aims to demonstrate how AI, and especially Generative AI, may empower LA to keep pace with the rapidly changing educational realm and stay true to its mission of understanding and advancing learning. In doing so, the paper relies on published empirical research in LA and closely related fields of AI in Education and Educational Data Mining. This evidence-based approach, inherent to LA, distinguishes the current paper from recent publications that discuss the opportunities and challenges of (Generative) AI for LA, and education more broadly, from a more hypothetical perspective.

II. Learning Analytics

A. What is Learning Analytics?

Learning analytics is 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" [1]. For a better understanding of LA, it is necessary to unpack this rather compact definition and highlight the key distinguishing features of LA as a research and practical field.

First, *data* are at the centre of any LA effort. LA uses a wide variety of data types and sources such as log data, self-reports, messages exchanged in distinct kinds of online communication channels, sensory data, etc. Amidst this variety of data types and sources, *learning traces* - also referred to as trace data or learning logs - remain the primary type of data in LA. Learning traces are data about learners' interactions with different (digital) learning resources, (online) learning activities, as well as other learners and teachers (e.g., communication in online discussion forums). The main advantage of learning traces compared to data traditionally used in educational research (e.g., surveys and think aloud protocols) is that learning traces can be collected seamlessly during the learning process, without putting any additional burden on learners and teachers. The continuous increase in the number and variety of software platforms and tools used in the learning process, as well as the continuously increasing adoption of online and blended learning both in formal and non-formal education, make learning trace data more and more available. This trend positively reflects on the relevance and the adoption of LA in practice.

In addition to learning logs collected in the context of online and blended learning, the collection of learning-related data in traditional classrooms and physical spaces in general, attracts more and more interest from LA researchers. This is made possible by the increasing availability of sensors (e.g., cameras, microphones, location-tracking sensors) that allow for measuring and collecting data about learners' interactions with a variety of physical objects used in learning, as well as data about mutual interactions of learners and teachers in different situations of collaborative learning. The collection and combined use of data from multiple sources, as well as advanced analytics such data enable, are in the focus of a subfield of LA known as Multimodal LA [2].

Another key construct in the definition of LA that requires further explanation is *optimization of learning and the environment in which learning takes place*, which is stated as one of the main objectives of the field. It is important to highlight that the term optimization in this context does not imply automatic adaptation of the learning process to a particular learner (e.g., automated personalization of learning), as is the case in closely related fields of Artificial Intelligence in Education and Educational Data Mining. In LA, optimization means that the results of analytics, such as insights about a learning process or recommendations, are communicated to learners and/or teachers, and it is left to them to decide how to act on the feedback received. Acting on the feedback in case of mature learners may take the form of making adjustments to one's own learning approach, in accordance with the information and recommendations received. In the case of young learners, feedback is typically directed to the teacher to help them choose pedagogical interventions to better support their students. Simply put, in LA, it is important to include humans (students, teachers, parents, etc.) in the process of adaptation and improvement of learning, the concept often referred to as human-at-the-centre. This is in accordance with one of the most prevalent learning approaches in LA, namely self-regulated learning (SRL), which postulates that learner is an active agent who, in a learning process, first defines their goals, then chooses learning strategies and tactics to achieve those goals, and while acting in the direction of the goals, continuously monitors and evaluates their progress and adjusts the chosen strategies and tactics accordingly [3]. The primary role of LA is to support the learner at all stages of the learning process, providing evidence-based insights, recommendations, and guidelines. Furthermore, such an approach gives teachers the sense of being in control of their teaching work (instead of being replaced through automation), which facilitates technology adoption.

Finally, it is necessary to clarify the meaning of *learning context* in the LA definition, considering that this term has been assigned a variety of meanings in educational research and practice. In LA, learning context is often described as a specific combination of internal and external factors that may affect learning [4]. Here, a learner is considered the reference point, meaning that internal factors include everything that constitutes the internal state of the learner, such as emotional state, motivation, prior knowledge, cognitive load, etc. On the other hand, external factors include all that may affect learning and is external to the learner, i.e., the learner does not have direct control over (e.g., pedagogical design of the course, specific pedagogical approach of the teacher, class schedule, etc.).

All the above suggests that LA is an interdisciplinary field, at the intersection of fields focused on learning (pedagogy, educational psychology, educational technologies), analytics (computer science, statistics, artificial intelligence), and human-centred design (human-computer interaction).

B. Learning Analytics Cycle

Learning Analytics can be viewed as a cyclical process [5] with four key components: learners, data, methods, and actions (Fig. 1). A generic LA cycle goes through the phases of *i*) identifying the *learner(s)* and the context in which learning takes place; *ii*) collecting relevant *data*, *iii*) selecting and applying analytics *methods* appropriate for the given learner, learning context, and data, and *iv*) *acting* on the analytics results, often through different forms of pedagogical interventions. This cyclical model bears a lot of resemblance to the CRISP-DM model [6], widely adopted for Data Science (DS) projects. In fact, at the first encounter, LA might be considered as the application of DS in the educational domain. Nonetheless, while the focus on data and computational methods are common to both LA and DS, the two fields differ in some important ways. First, in DS, the primary focus is on the development of high-performance computational models (e.g., prediction models), with less attention to the theoretical grounding of the model and the ability to explain the phenomena being modelled (e.g., learners at risk of failing a course). On the other hand, LA is focused on supporting evidence-based decision making of distinct participants in the learning process. Therefore, in LA, the development of computational models is first and foremost led by the objective of understanding the learning process. That understanding serves as the basis for acting, that is, taking pedagogical interventions. Henceforth, in LA, model development needs to be grounded in sound pedagogical theory and informed by the specificities of the learning context. Learning context has been recognised as particularly important in model development and results interpretation [7]-[9]. Likewise, to offer grounds for pedagogically sound interventions, both research questions and methodologies need to be theoretically grounded in well-established learning theories. In short, LA research is not data-driven, as it is often the case in DS, but it makes use of data in a manner shaped by the appropriate learning theory and particularities of the learning context. Furthermore, the importance of understanding a computational model and what can be learnt from it about the learning process and / or learners, is the reason why LA often relies on relatively simple machine learning models, while deep learning models have been rarely adopted.

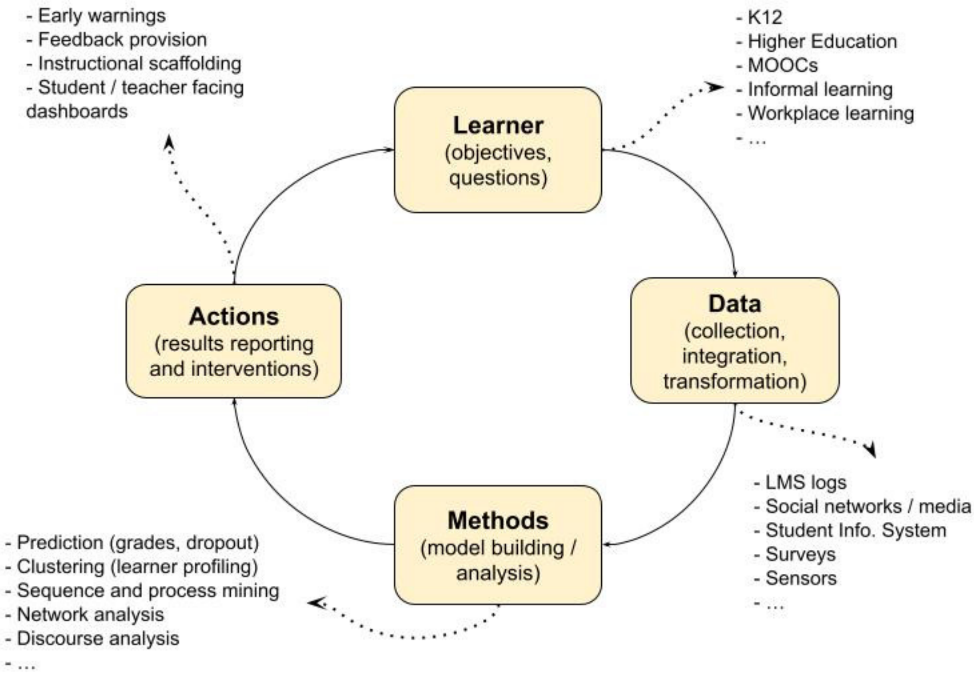

Fig.1 The cyclic Learning Analytics model

Fig. 1 illustrates the cyclical LA model and its key components. Since the overall objective of LA is to understand and optimise learning and the environments in which it occurs, any LA effort starts with identifying *learner(s)* and the learning context to be studied. This ensures that all the subsequent phases of the LA cycle are driven by the objective to support and/or advance learning for the given learner(s) and the given learning context [10]. As AI tools are becoming increasingly present in learning and workplace environments, researchers have started exploring concepts such as hybrid intelligence [11] and hybrid human-AI regulation of learning [12], and some argue for a renewed understanding of the notion of learners, one that integrates the AI dimension [13]. While such altered conceptualization of learners opens interesting research pathways, it goes beyond the scope of the current paper and interested readers are referred to [13] to explore more.

The *data* component refers to the collection, integration, and transformation of data. As already noted, LA relies on data from diverse and often multiple sources, among which the most typically used include learning platforms and tools as well as platforms and tools that may be used for learning (e.g., online social networks and social media); student information system, in case of formal education; various kinds of surveys, often administered before and/or after the studied learning process; sensors such as devices for eye-gaze tracking, position tracking, and video recording of learning [14]. The use of a variety of data, often in a combined manner, allows for comprehensive insights into the learning process. Furthermore, triangulation of data from multiple sources contributes to the trustworthiness of the conclusions derived from the data. However, access to multiple data sources is still a privilege of studies done in controlled settings. In natural learning settings, learning trace data still remains if not the only, then the dominant data source.

The *methods* component refers to a variety of quantitative and qualitative methods that are used in LA research. The most dominant among LA methods are those based on AI, namely on machine learning and natural language processing. Such methods have been used for predictive modelling (e.g., prediction of students' performance in a course or a study program), learner clustering (e.g., learner profiling based on indicators of engagement with course resources and activities), discourse analysis (e.g., analytics of messages exchanged in online communication channels) [10], [14]. Different kinds of network analysis have been used as well. Social network analysis and epistemological network analysis have been primarily used for developing a better understanding of the structure and content of interactions among actors in the learning process [15], whereas psychological networks have been used for studying both static and dynamic characteristics of learners' psychological states [16]. Process and sequence mining, often combined with advanced statistical modelling, have been used to study the dynamics of learning processes, especially self-regulated learning [14], [17].

Finally, the *actions* component refers primarily to the communication of insights obtained through analytics to relevant stakeholders (learners, teachers, program coordinators, etc) and pedagogical interventions. The communication of analytics results is often done through LA dashboards [18], that is, tools that present LA findings, often in the visual form, in order to support informed decision-making and, in case of learner-facing dashboards, to trigger the desired behavioural change. The action may also take the form of pedagogical interventions, aimed at changing the instructional design and/or offering support to learners (e.g., through different kinds of pedagogical scaffolds) based on the evidence obtained through analytics.

This cyclical model of LA will be used in the next section as the framework for examining the interplay of LA and AI. In particular, by relying on the findings of recent empirical work in LA and related fields of Educational Data Mining and AI in Education, we will explore how key LA components relate to and may benefit from the latest developments in AI, and especially Generative AI.

III. The interplay of Learning Analytics and Artificial Intelligence

This section explores the interplay of LA and AI from the perspective of data, methods, and actions components of the LA cyclic model. For each component, we present how it has been advanced through the use of AI and / or how it has been used to better understand the role / impact of AI on learning. Note that the learner component is not considered due to the paper's focus on the empirically explored and evidenced interaction of LA and AI, and such efforts, so far, have been based on unaltered notion of learner.

A. Data

Learning traces have been used in a wide variety of LA tasks, most often for predictive modelling and detection of behavioural patterns reflective of the adopted learning tactics and strategies[1]. For example, using learning traces from a Coursera course, Jovanovic et al. [16] identified three distinct patterns of learners' interaction with the course activities during individual learning sessions. By considering the visual representation of the identified patterns (Fig. 2) from the perspective of the course design, three learning tactics were identified: assessment-oriented, mastery-oriented, and mixed. These tactics were then used to cluster learners, to identify strategy-based learner profiles. This and similar analysis of learning traces allow LA researchers to understand how learners approach distinct learning and assessment tasks. In other words, analytics of learning traces allow for answering the "what" question – e.g., what learning tactics and strategies a learner has chosen in a course or a module within the course. However, learning traces alone do not allow for answering the "why" questions related to the detected tactics and strategies. These include questions such as why a particular tactic or strategy was selected for the given learning task? Why did a learner switch from one tactic to another and why in a particular moment in time? To answer such questions, data about the learner's internal state (e.g., perceptions, intentions, motivation) are needed.

Some recent studies have also empirically demonstrated the relevance of learner internal factors in predictive modelling. For example, the study presented in [9] analysed a large number of potential predictors of students' academic success (i.e., indicators of academic success derived from trace data), in order to identify predictors that would be relevant across several courses in a study program and thereby, at least partially, enable cross-course portability of predictive models. The study relied on learning traces from a large, homogeneous sample of courses from a healthcare degree program (15 distinct courses, with 50 course offerings). The study results show that behaviour-based indicators explain only a very small percentage of the variability in student achievement, while a significant portion of the variability comes from the students' personal (internal) characteristics. This and similar studies confirmed the intuition about the importance of considering factors characterising learners' internal state when building LA models.

Data about Learner's Internal States. While the relevance of learners' internal factors has been well recognised, collection of data about such factors is still a challenge. Traditionally, such data have been collected through self-reports in the form of surveys, often administered at the beginning and / or

[1] Learning tactic refers to a specific cognitive routine that a learner adopts when solving a particular learning task, whereas a learning strategy is a specific way the learner selects, applies, and modifies learning tactics when working towards a set learning goal.

at the end of a course. However, such data collection approaches do not allow for capturing the dynamics of learners' motivation, emotions, goal orientations, cognitive load, and other relevant internal factors [19], [20]. In a systematic literature review of LA as a research field, Dawson and colleagues have well recognised challenges associated with learner data collection and noted that "despite the recent advances in multimodal LA, data concerning social and personal dimensions such as motivations, emotions, health and culture are reliant on self-reports or collected from expensive and intrusive equipment" [21]. Current LA research seeks to overcome this challenge through a variety of approaches that all share a common trait, namely the reliance on non-intrusive methods and tools to collect real-time longitudinal data about learners' internal state. As outlined below, some of these approaches rely on human computer interaction to collect data directly from learners, whereas other leverage AI to indirectly obtain (i.e., extract) data about learners' internal states from traces of learner actions and interaction artefacts.

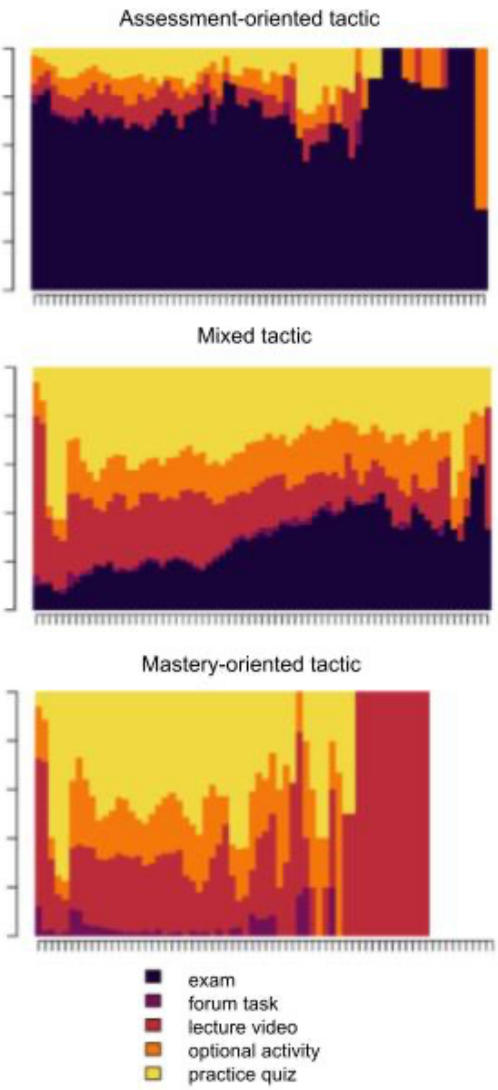

Fig. 2 Illustration of distinct patterns of learners' interaction with course activities, reflective of the adopted learning tactics [16]

Ecological momentary assessment (EMA) is a specific protocol for systematic, longitudinal collection of data about individuals' internal states, by asking a few quick questions in regular time intervals over a longer period of time (e.g., a few weeks or a few months) [22]. Such a protocol is typically operationalised through a mobile phone app, which allows for easy data collection. For example, Fried and colleagues [23] applied EMA to collect data on the psychological and emotional state of students during the first few months of the COVID19 pandemic, and used network analysis to timely identify factors that may cause mental health problems. More recently, Saqr et al [24] used data collected through EMA to build predictive models of distinct self-regulated learning dimensions (e.g., effort regulation, metacognition, motivation and emotions) for individual students. This study also exemplifies an increasing interest of LA research in idiographic analysis, that is, analysis focused on individual students (N=1), as it has been shown that conclusions derived from cohort level analysis rarely apply to individual students [25], [26].

As an alternative to direct data collection from learners, LA researchers have also explored the use of AI to automate real-time detection of learners' affective states and emotional engagement, using either trace data alone or traces combined with messages exchanged in online communication channels. An interesting example of the former approach is the work of Hutt et al. [27] who used domain- and platform-independent activity features (e.g., viewing a video lecture, taking a quiz, accessing the discussion board) and state-of-the-art machine learning algorithms to identify 18 distinct emotional states. The authors collected a very large dataset (traces from 69,174 students in 1,898 U.S.A. schools over an entire school year) and built predictive models of learners' affective states that generalised to new students across the two examined domains. However, the models' accuracy was still far from the desired. On the other hand, Liu et al. [28] proposed a state-of-the-art text classification model (BERT-CNN) to identify emotional engagement (positive, negative, confusion) of students in a Massive Open Online Course (MOOC), starting from messages exchanged in the MOOC's discussion forum. While the presented model outperformed alternative models, further improvements are needed before such a model can be used as a trustworthy source of information about learners' emotional engagement in a learning task.

Sophisticated conversational agents, enabled by the latest generation of Generative AI, promise to offer a viable alternative to traditional self-reporting instruments for the collection of data about learners' internal state. By engaging learners in a conversation, instead of presenting them with often long and dull surveys, a chatbot-based data collection approach may prove to be both enticing and effortless and thus increase response rates and quality. To our knowledge, there are still no empirical results on such uses of conversational agents in educational contexts. However, as agent capabilities required for such a task (e.g., proactiveness, goal awareness) are the subject of active research (see e.g., [29]), it is realistic to expect the use of conversational agents as means of collecting self-reports data in a more natural and enticing manner.

Data Privacy. Data sets used in LA research and practice often contain sensitive data (e.g., student grades, student IP addresses, indicators of psychological and/or physiological state). Data about learners' internal states, discussed above, represent a particularly sensitive category. As the collection of sensitive data increases, concerns regarding privacy protection grow, as well. In general, the continuous increase in volume and diversity of data being collected in educational settings as well as the growing potential for data misuse through the use of advanced technologies (AI included), have made data privacy an area of high concern for LA practice and high relevance and priority for LA research [30].

Traditional approaches to data anonymization have proven insufficient, signalling the need for more robust approaches. For example, it has been shown that unsupervised machine learning techniques can be used to access sensitive student data, despite data anonymization prior to its publishing [31]. An additional challenge is that traditional approaches to protecting data privacy often come at the expense of data utility for LA [32]. In particular, as data privacy increases, data utility, as reflected, for example, in the accuracy of predictions based on that data, declines significantly. All of the above, as well as the general consensus on the need for ethical and responsible use of data in LA, both legally and socially, have led to an increased interest in more robust forms of data anonymization.

Synthetic data represents a state-of-the-art solution for preserving data privacy in highly sensitive domains, such as education, health, and finance [33]. To preserve data privacy, synthetic data, generated by mimicking the characteristics of the original data, is made publicly available instead of the original data. Recent research has demonstrated that, unlike earlier approaches to educational data protection, the use of synthetic data meets the requirements of both data utility and privacy (see, for example, [32], [34]). Sharing of educational data, enabled through the use of synthetic data, is highly important for LA research since it is not unusual that due to the lack of data access, some research objectives need to be abandoned. Furthermore, data sharing is necessary for replication of published research, which is the cornerstone of Open Science.

It is important to mention that until recently, the generation and use of synthetic data was largely limited to structural data, namely tabular data and time series. However, the development of generative AI not only allowed for more sophisticated generation of structured data [33], but also opened opportunities for generating synthetic textual data and multimedia content. For example, to address the problem of limited training data for one-on-one tutoring system, Shan et al. [35] proposed a data augmentation pipeline that leverages Generative AI (GPT-3.5) to create synthetic, multi-labeled dialog data. Similarly, to address limited training data for grounded dialog systems (e.g., tutoring agents), Bao et al. [36] proposed a synthetic data generation framework for grounded dialogues, which leverages Generative AI (T5) to transform the given dialog flow (i.e., a sequence of knowledge pieces to be covered in a dialog) into a fluent dialog.

Another recent approach to protecting student privacy is to use large language models to identify and remove personally identifying information (PIIs) from messages exchanged in online communication channels. An example is a recent work by Singhal et al. [37] that assessed GPT-4's performance in de-identifying data from discussion forums in nine MOOCs. Overall, the results show high recall (0.958), but low precision (0.526). The tool proved highly successful in identifying PIIs, even identifying cases missed by humans when redacting data. However, it over-redacting names and locations that do not represent PIIs.

B. Methods

From the perspective of LA methods, the interplay of LA and AI comes in two main forms: 1) the use of AI to augment or facilitate LA modelling / methodological approaches, and 2) the use of LA methods to study AI-human interaction in various learning contexts.

Regarding the former aspect of the LA-AI interplay, some methods often used in LA, such as discourse analysis and epistemological network analysis, require qualitative coding of textual content exchanged in learning related interactions (e.g., messages exchanged or comments shared in a collaborative learning task). Qualitative coding has traditionally been a manual task, requiring a lot of time and effort. The latest generation of large language models (LLMs) has provided solid technological grounds for exploring the potentials of semi- or fully automating this task. For example, Hou et al. [38] explored the effectiveness of prompt engineering and fine-tuning approaches for deductive coding of social annotations. In deductive coding, the categories (codes) to be used in the coding task are predefined and often originate either from a relevant theoretical framework or prior empirical research. Categories used for coding can be context dependent or context independent. Context-independent are those categories for which access to individual pieces of content (e.g., a message or a comment) is sufficient to do the coding. On the other hand, context-dependent categories require understanding of the given piece of content in relation to contextually related pieces of content (e.g., previous messages or some external materials), to properly do the coding. In their study, Hou and colleagues [38] considered both kinds of codes and examined the performance of GPT-3.5-turbo adapted to the coding task through prompt engineering or fine tuning. The study results demonstrated that prompt engineering enabled fair to substantial agreement with expert-labelled data across various coding dimensions. Somewhat better results, that is, higher level of agreement, were achieved with fine tuning. As was expected, in both cases, agreement was higher for context-independent than context-dependent categories. In a related study, Barany et al. [39] explored the role that could be played by LLMs, specifically GPT-4, in the process of developing a codebook for a qualitative coding task, that is, establishing a set of categories to be used for qualitative coding. This is, again, a task that has been done exclusively by researchers. The study compared four approaches to codebook development – a fully manual approach, a fully automated approach, and two approaches that relied on GPT-4 within specific steps of the codebook development process. The study findings suggest that GPT-4 can be valuable for improving qualitative codebooks for use in educational research, but human participation is still essential.

The other form of interchange between LA and AI, namely the use of LA methods to study the interaction of humans and AI in learning situations, is well exemplified in a recent study by Fan et al. [40]. In particular, to examine how students' interaction with Generative AI during an essay revision task compares to interaction with other, more traditional forms of support, Fan and colleagues conducted an experimental study in which they randomly split students into four conditions: one control (no support) and three experimental conditions, each corresponding to a distinct form of support offered during the essay revision task: (human) teacher, ChatGPT, and a checklist suggesting things to focus on when revising the essay. To examine students' interaction with these distinct means of support, the researchers collected learning traces, namely log data, mouse movements, keyboard interaction data, and eye gaze data. The collected traces were parsed into micro-level learning (cognitive and metacognitive) processes which were further analysed through process mining to reveal differences in how interaction with the available help unfolded over the task. This analysis revealed different patterns of interaction with distinct sources of support. In the ChatGPT group, the dominant pattern had a form of back-and-forth between the use of ChatGPT and the very task of revising the essay, whereas other cognitive (e.g., (re-)reading) and metacognitive (e.g., orientation, evaluation) processes were almost absent. On the other hand, the group that interacted with the human teacher did not inhibit, but rather enhanced, connections between essay revising and other learning processes. Furthermore, while the ChatGPT group had significantly higher scores on the revised essays compared to the other conditions, the conditions did not significantly differ in terms of knowledge gain and transfer, nor in the task motivation. Overall, the study findings suggest potential problems of over-reliance on Generative AI and metacognitive laziness, the latter meaning that, when interacting with Generative AI, students tend to leave their metacognitive capacities (monitoring, evaluation, adaptation) dormant. Similar conclusions were reported by Darvishi et al. [41] based on a large randomised controlled study (1625 students across 10 courses). Using LA methods, the study examined if students would learn from regular, detailed, and personalised feedback provided by an LLM-based assistance tool, so that they would be able to exhibit similar behaviour when the assistance is not available. The results showed that students were able to effectively self-regulate their learning with the AI assistance, but with the removal of this support, their performance significantly dropped. In other words, the students tended to rely on rather than learn from the AI assistance. This and similar findings suggest that with the increasing presence of AI in education, pedagogical interventions that motivate student agency and collaboration with (instead of pure reliance on) AI will be increasingly needed.

A follow-up of the abovementioned study by Fan and colleagues, employed LA methods to examine students' interaction with the human teacher and ChatGPT from the help-seeking perspective [40]. In particular, screen recordings of the students' exchanges with the teacher or ChatGPT were (manually) coded based on the adopted help-seeking theoretical model and the resulting codes served as the input to temporal analysis (process mining) of student - teacher / ChatGPT communication. The resulting process models suggested very different patterns of help-seeking: compared to the human teacher group, in the ChatGPT group, learners asked more "executive" questions (i.e., questions focused on getting direct solutions), and accepted ChatGPT's assistance as is, without evaluation. Furthermore, the students' self-reports after the study revealed lower "social cost" in the ChatGPT group compared to the group working with the human teacher. In other words, students reported being more at ease to seek help from ChatGPT as there were no risks of embarrassing oneself.

Another interesting example of using LA methods to better understand students' use of Generative AI is the study by Brender et al. [42] that examined distinct patterns of student interaction with ChatGPT in the context of a graduate-level robotics course. By clustering students based on the features derived from prompts that students wrote when seeking help from ChatGPT, the researchers identified three profiles (clusters) of ChatGPT use that differed in terms of learning and task performance: i) Debuggers, who requested solutions and error fixes; ii) Conceptual explorers, who sought to understand concepts, tasks, or code, and iii) Practical developers, who exclusively asked for task solutions. While Debuggers had the best task performance, like Practical developers, they were less likely to translate performance into conceptual understanding. On the other hand, Conceptual Explorers had better overall learning outcomes compared to the other two profiles. This study offers yet another confirmation that over-reliance on Generative AI, while often beneficial for short-term performance goals, may inhibit a true mastery of new knowledge and skills.

LA researchers are also experimenting with AI-based pedagogical interventions that include student interaction with more than one AI-based agent. For example, an ongoing study in the domain of medical education enrols two LLMs in the task of helping student doctors to learn how to talk to a patient [40]. In particular, one LLM is acting as a patient, whereas the other takes on the role of a senior medical doctor "observing" the interaction between the "patient" and the student doctor and providing feedback to the student.

Finally, there are some nascent approaches to using LA to assess human-AI collaborative work. These have been motivated by the recognition that AI systems and tools are becoming an intrinsic part of various kinds of professions and that the future of work would include different forms of human-AI collaboration. Hence, it will be the task of education to help learners develop knowledge and skills required for a thriving human-AI collaboration as well as to assess such collaboration. The assessment of human-AI collaboration includes not only evaluation of the outcome of a collaborative task, but also evaluation of the processes that led to those outcomes [43]. An example of this line of research is a recent work by Cheng at al. [44] that proposed a LA-based method for assessing collaborative writing of humans and Generative AI. The method relies on learning trace data collection, their mapping to learning processes, and finally epistemological network analysis of student-AI exchanges.

C. Actions

Learning analytics dashboards are a primary method for delivering analytics results to end users, thus facilitating evidence-based decision-making and actions. However, a persistent challenge has been communicating LA feedback in a way that end users, who may lack technical expertise, can accurately interpret and act upon [18]. To address this challenge, researchers have explored ways for augmenting LA dashboards with Generative AI. For example, Yan et al. [45] proposed VizChat, an open-sourced, prototype chatbot designed to augment LA dashboards with contextualised, AI-generated explanations of visually presented LA results. The objective is to improve user comprehension of the dashboard without overwhelming the user with excessive information. To that end, VizChat leverages multimodal Generative AI (GPT-4V) and Retrieval Augmented Generation (RAG) to offer on-demand, contextually relevant explanations of specific visualisations as well as a summary of information integrated from multiple visual depictions of LA results. To increase the transparency and contribute to trust in the feedback communicated through the dashboard, the tool also offers detailed information about the data sources used and analytics processes behind each visualisation. Still, the informativeness and usability of VizChat has yet to be verified through more comprehensive empirical studies with students and teachers.

Another interesting approach to advancing communication of LA feedback is storytelling augmented with Generative AI. The use of storytelling either as an alternative or a complement to LA dashboards has already been explored (e.g., [46]), especially in the context of multimodal LA, where, due to the use of multiple data sources, the challenge of clear results communication is especially high [47]. Aiming to further facilitate communication of LA feedback to learners and make it more appealing, Milesi and colleagues [48] explored the combined use of Generative AI and data comics, the latter being an emergent storytelling format for helping end users (non-expert) understand complex data and analytics. In particular, the researchers used MidJourney, an image generation AI tool, and a graphics illustration tool to create personal data comics about students' multimodal LA data. The initial evaluation of this approach with nursing students showed that while students found Generative-AI-augmented data comics appealing and enjoyable, they also expressed concerns that such a form of communicating insights from data lack the professionalism required for the given learning context (professional education). While probably not suitable for adult learners, this approach holds promise for young learners.

A well-recognized limitation of LA dashboards is the unidirectional communication of LA data and feedback. Research on educational feedback has shown that such (one-way) communication of feedback is far from optimal [49]. What is preferable is a dialog form, that is, bidirectional communication that allows for better dealing with any potential problem revealed through analytics or resolving any potential misinterpretation of the originally communicated analytics findings. Conversational chatbots, enabled by Generative AI, have opened opportunities for engaging students in such dialogic feedback. Rich literature on pedagogical agents [50], which predates the recent Generative AI developments, may offer strong foundation for such conversational agents. However, at the point of writing this manuscript, empirical findings that may confirm the expected benefits of Generative AI for dialogic feedback provision are still lacking.

Some recent studies have examined the use of the latest generation of LLMs for automated generation of feedback on student produced content, with the ultimate objective of helping students improve their writing. For example, Hutt et al. [51] examined the use of ChatGPT for providing students with feedback on peer feedback, that is, helping students learn what constitutes "good" feedback and how to provide it[2]. To understand the potentials of the latest generation of LLMs compared to earlier AI-based solutions, Hutt and colleagues compared ChatGPT with traditional text classification models in estimating the quality of peer feedback, according to the given rubric. The traditional AI models proved more accurate, while the advantage of ChatGPT was that it produced explanations of the assigned quality category.

IV. Conclusion

This paper explored the interplay between Learning Analytics (LA) and Artificial Intelligence (AI), as evidenced in recent LA research. It highlighted both the benefits AI has brought to LA and the ways in which LA has been used to enhance our understanding of AI's role and impact on learning, particularly with Generative AI. All this suggests that LA community has made significant contributions both in:

- using AI to address long-standing challenges in LA research, such as ensuring data privacy and advancing LA dashboards.

[2]Peer feedback is considered a powerful learning strategy as it offers learning opportunities both for the learner receiving feedback and the learner providing feedback. However, students often lack knowledge regarding what constitutes "good" feedback and need to learn how to provide it.

- using LA to gain insights into learners' interactions with AI, such as identifying learners' tendency to over-rely on AI and neglect metacognitive processes.

AI introduces new opportunities and challenges for LA research while also equipping researchers with more advanced methods, richer data, and improved ways of communicating analytics results, such as explanations and dialogic feedback. The dynamic between LA and AI promises to continually yield relevant insights into the evolving role of AI in learning. For these insights to be effectively integrated into educational practice, the active engagement of all stakeholders is crucial, alongside public policies that recognize the importance of timely, evidence-based decision-making in the era of Generative AI.

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