Chapter 2
Adapting Teaching and Learning in Higher Education Using Explainable Student Agency Analytics

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ABSTRACT

This chapter deals with the learning analytics technique called student agency analytics and explores its foundational technologies and their potential implications for adaptive teaching and learning. Student agency is vital to consider as it can empower students to take control of their learning, fostering autonomy, meaningful experiences, and improved educational outcomes. Beginning with an overview of the technique, its underlying educational foundations, and analytical approaches, the chapter demonstrates the synergy between computational psychometrics, learning analytics, and educational sciences. Considering adaptive artificial intelligence in the context of adaptive learning and teaching, the chapter underscores the potential of these approaches in education. The chapter serves as a brief guide for educators, researchers, and stakeholders interested in the convergence of AI and education.

DOI: 10.4018/979-8-3693-0230-9.ch002

1. INTRODUCTION

In the rapidly evolving landscape of higher education, the role of student agency has emerged as a key element in shaping meaningful and intentional learning experiences (e.g., OECD, 2019; Stenalt & Lassesen, 2021; Vaughn, 2020). In light of the global digital transformation phenomenon (Mukul & Buÿüközkan, 2023), educational institutions increasingly acknowledge the need to leverage data to enhance educational processes and outcomes (e.g., Banihashem et al., 2022). Recent research, including studies on the role of student agency in pedagogical decision-making (Heilala et al., 2022), course satisfaction in engineering education (Heilala, Saarela, et al., 2020), and the experiences of students with limited agency resources (Heilala, Jääskelä, et al., 2020), underscores the importance of this approach. The findings from these studies suggest associations between student agency and various educational outcomes. This chapter aims to shed light on the transformational potential of adaptive artificial intelligence (AI) in the context of higher education, drawing on recent research that explores student agency and its influence on instructional practices.

Student agency analytics (Jääskelä et al., 2021) represents a novel approach in higher education research, which focuses on making explicit students' capacities for intentional and meaningful learning under the power and participatory structures in the learning context. This method integrates the principles of learning analytics, which involves collecting, analyzing, and reporting educational data to improve learning design (Conole, 2011), with the study of student agency. In this context, agency refers to students' capacity to take control of their learning and utilize personal, relational, and participatory resources that allow a student to engage in purposeful, intentional, and meaningful action and learning (Jääskelä et al., 2017; Jääskelä et al., 2023). The application of student agency analytics offers a data-driven lens to understand and support students' learning experiences. By leveraging machine learning and psychometrics techniques, this approach provides educators with actionable insights into students' agency resources. These insights can adapt teachers' pedagogical decisions, learning environments, and educational interventions (e.g., Heilala et al., 2022). Recent research has also explored students' experiences with varying levels of agency resources using explainable methods, revealing factors such as competence beliefs, self-efficacy, and student-teacher relationships as influential determinants (Saarela et al., 2021).

This chapter provides an interdisciplinary overview of student agency analytics, its foundational principles, and the implications of integrating artificial intelligence in education (AIED). Reviewing current research and empirical findings, the chapter will clarify the potential of adaptive AI in enhancing student agency in higher education. As higher education institutions continue to embrace digital transformation, student agency analytics can emerge as a valuable tool for fostering student-centered learning environments. By understanding and addressing the unique needs of students, this synergy could pave the way for more personalized and effective educational experiences.

2. BACKGROUND

This section outlines the concept of agency, briefly exploring its philosophical origins and evolution in contemporary thought. A particular emphasis is placed on student agency, a specialized facet of the broader agency construct, highlighting its significance in shaping students' learning experiences. The section further introduces the novel technique of student agency analytics, a learning analytics approach that seeks to quantify and analyze students' agency within educational environments. By integrating computational methods and ethical considerations, this section offers an overview of how student agency analytics can provide valuable insights for educators and learners, fostering a more intentional and meaningful learning experience.

2.1 Starting With the Construct: On Agency

In its broadest sense, agency encompasses the capacity for intentional action and change. Historically, the concept of agency has deep philosophical roots, tracing back to thinkers like Hume and Aristotle (Schlosser, 2015). In contemporary analytic philosophy, the works of Anscombe (1957) and Davidson (1963) have been particularly influential, focusing on the intentionality of actions. According to the standard conception, a being possesses agency if it can act intentionally (Schlosser, 2015). This intentional action is often tied to instantiating certain mental states and events, such as desires, beliefs, and intentions, leading to specific outcomes or behaviors. Schlosser (2015) further elaborates on this by suggesting that a being's capacity to act intentionally is contingent upon its functional organization, where specific mental states cause particular events in a defined manner.

The concept of agency extends beyond individual intentionality and is deeply intertwined with social and relational contexts. Emirbayer and Mische (1998) emphasized the temporal and relational aspects of human agency, suggesting that it involves a dynamic interplay between habit, imagination, and judgment, all set against changing historical situations. This perspective underscores the importance of understanding agency as a product of individual intentions and broader structural environments. Furthermore, the post-humanist viewpoint expands the boundaries of agency beyond humans, suggesting that non-human entities, such as animals, algorithms, and pedagogical agents (Baylor, 1999; Jamieson, 2018; Peeters, 2020; Sikström et al., 2022), can also possess varying degrees of agency. This broader view challenges traditional notions and invites a more inclusive understanding of agency, encompassing human and non-human actors in diverse contexts. Bryant (2021) suggested the concept of augmented agency, which refers to the synergistic collaboration between human and artificial agents, blending humanized and digitalized processes to achieve emergent outcomes. Reaching beyond mere understanding of data and data literacy, Tedre and Vartiainen (2023, p. 1) pointed out the importance of data agency that refers to "people's volition and capacity for informed actions that make a difference in their digital world" and emphasizes managing and using data responsibly and ethically (Vartiainen et al., 2022).

Matthews (2019) highlighted the postdigital perspective as a lens to understand the intertwined nature of digital and non-digital technologies in society and culture. In higher education, this lens offers a critical approach to the use of digital technology, emphasizing the agency of all actors involved in learning and teaching activities. As Fawns (2019, p.132) pointed out, while "concepts like 'digital education' can be useful insofar as they encourage people to look closer at the design and practice of teaching and learning, they become problematic when used to close down ideas or attribute essential properties to technology." The actor-network theory (ANT) (e.g., Akrich, 2023; Silvast & Virtanen, 2023) within this perspective underscores the interconnectedness of human and non-human actors, advocating for inclusive design in learning environments. For example, Martin et al. (2020) examined intricate networks formed between learning analytics platforms (LAPs) and educational actors, emphasizing LAPs' performative roles and their influence on shaping educational futures and practices.

Student agency, a specialized subset of the broader concept of agency, pertains specifically to individual, institutional, and societal antecedents and outcomes of agency within educational settings (Stenalt

& Lassesen, 2021). Rooted in the foundational principles of agency, which emphasize intentionality and action, student agency encapsulates the ability of students to take control of their learning, make informed decisions, and act upon them (e.g., Lim & Nguyen, 2023). This means that students, equipped with agency, not only act with intention but also navigate, influence, and shape their learning trajectories based on their desires, beliefs, skills, and intentions (Klemenčič, 2017; Mameli et al., 2021; Membrive et al., 2022; OECD, 2019). However, student agency is not just about individual intentions but also about how students interact with the curriculum, pedagogical approaches, and the broader educational environment and are empowered to act through this interaction; thus, subjective experiences play a key role in defining the state of one's agency (e.g., Jääskelä et al., 2020; Jääskelä et al., 2023).

The concept of student agency is multifaceted, influenced by both individual characteristics and broader educational structures. Drawing parallels with the broader concept of agency, which is deeply embedded in social and relational contexts (Bandura, 2001), student agency is also shaped by the interplay between individual students and the educational systems they inhabit (e.g., Klemenčič, 2015). For instance, while students might possess the intrinsic motivation to learn (akin to individual intentionality in general agency), the educational environment, pedagogical approaches, and curriculum can either foster or hinder the expression of this agency (e.g., Gale et al., 2022; Groenewald & le Roux, 2023; Jääskelä et al., 2020). Also, students within the same course have highly varying experiences of their opportunities to practice agency in the course; for example, someone may feel that there are plenty of opportunities to influence the course progress, but instead, another student perceives the same situation in the opposite way (Jääskelä et al., 2022; Jääskelä et al., 2018) Furthermore, as with the post-humanist perspective on agency, student agency also extends beyond individual actions, e.g., as sociomaterial agency (Nieminen et al., 2022). It encompasses collaborative endeavors, where students work interactively, influencing and being influenced by peers, educators, technology, and the broader educational ecosystem (e.g., Charteris & Smardon, 2018; Gale et al., 2022; Stenalt, 2021). This dynamic nature of student agency underscores its complexity, making it a pivotal area of exploration in modern educational research utilizing recent technological advances.

Based on their multidimensional construct analysis, Jääskelä et al. (2020), Jääskelä et al. (2017), Jääskelä et al. (2023) developed a measurement, Agency of University Students (AUS) scale, which captures students' perceptions of their agency in three resource domains in the course context: personal, relational and participatory domains. Personal domain centers on students' self-efficacy (overall confidence as learners) and competence beliefs (e.g., concerning understanding the course contents) emphasized in the literature of the social–cognitive sciences (e.g., Bandura, 2001; Bandura, 2006; Schunk & Zimmerman, 2012). The relational domain focuses on students' experiences of safe and fair student-teacher relationships, for example, the extent to which a student can trust teachers, have support from them, and experience that one is being treated equally in relation to other students in the course; the aspects highlighted especially in the educational literature (e.g., Eteläpelto & Lahti, 2008). The participatory resource domain considers actualizing agency as multilevel interactions between the individual and the environment. In this interaction, individuals shuttle between their own desires, intentions and personal learning needs, and institutionalized structures, norms and practices (Berger & Luckmann, 1966), for example, objectives of the curriculum, the established course practices, traditions to teach and learn, and expectations of student role. Agency is optimally realized as a student's interest and enthusiasm for learning when teaching, materials, or methods resonate with one's learning goals, and a student can perceive the utility value in gaining goals (e.g., Wigfield et al., 2019). It is also realized as students' active participation in common tasks and knowledge construction when learning situations include space for dialogue with others (e.g., Lipponen & Kumpulainen, 2011). Furthermore, participatory agency is about having opportunities to be involved in the decision-making concerning the progress of the course. The AUS Scale utilized in the student agency analytics was previously validated as an 11-factor model with the data collected from university students at a Finnish University (Jääskelä et al., 2020). The dimensions (factors) are Self-efficacy and Competence beliefs (representing the personal domain), Trust for the teacher, Teacher support and Equal treatment (relational domain), Participation activity, Ease of participation, Interest and utility value, Opportunities to influence, Opportunities to make choices, and Peer Support (participatory domain) (see, Jääskelä et al. (2023)).

In summary, the concept of agency, rooted in philosophical and sociological thought, encompasses individual intentionality and the capacity to act within broader social contexts. Student agency emerges as a specialized mindset when specified in the educational sphere, emphasizing students' capacity to navigate and influence their learning experiences by utilizing different agentic resources. Empirical knowledge of student agency is needed to increase understanding of student agency as a multidimensional construct. The technique referred to as student agency analytics utilizes learning analytics procedures to gain a more comprehensive understanding of how students exercise their agency within educational environments. In the following section, a review will be given of the details of student agency analytics, its basic principles, and its ability to bring about beneficial changes in ways of teaching and learning.

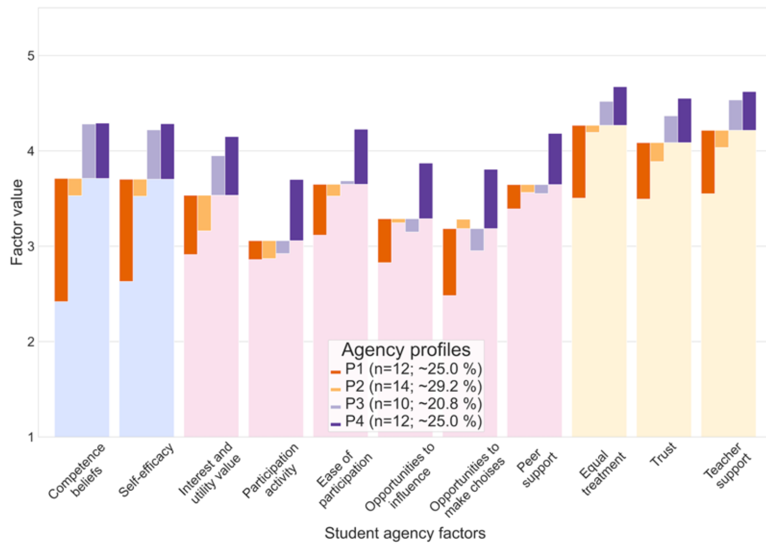
2.2 From Construct to Application: On Student Agency Analytics

Student agency analytics is a novel technique in learning analytics—at the intersection of educational research and data science—focusing on understanding and enhancing students' intentional and meaningful learning resources (Jääskelä et al., 2021). At its core, this approach seeks to quantify and analyze the ways in which students exercise their agency within educational settings. This data-driven perspective offers insights into individual students' learning experiences and also sheds light on broader patterns at the group level, in addition to suggesting potential areas of pedagogical intervention (Heilala et al., 2022). From the learner's point of view, obtaining prompts for self-assessment is an expected feature of learning analytics (Schumacher & Ifenthaler, 2018). Thus, student agency analytics also aims to provide students with a means for self-reflection.

The process can be visualized as a cyclical flow (Figure 2). It begins with the teacher's initial instructional planning. As the teaching progresses, students fill out the AUS survey, triggering the automatic execution of agency analytics. Once the results are available, teachers can refine their instructional strategies based on the students' reported agency resources. The main advantages of student agency analytics include 1) its foundation in theory related to student-focused learning, 2) its capability for automated analysis suitable for moderate group sizes, 3) its use of an innovative visualization to present results to educators, 4) its commitment to protecting student privacy, 5) its demonstrated associations with positive emotions (such as course satisfaction) and learning outcomes, and 6) its utility for educators in reflecting on and making pedagogical decisions (Heilala, 2022).

The data collection in student agency analytics involved using the AUS scale (Jääskelä et al., 2017; Jääskelä et al., 2023), a questionnaire described in the previous section that is designed to measure students' agentic resources in different educational contexts in higher education. The scale was provisioned as an online questionnaire that can be used in various settings, from online environments to in-person situations. In the case of student agency analytics and discrete Likert type of data, preprocessing was a straightforward operation involving data pseudonymization for increased privacy and security and data imputation in case of missing values. After the data are in a form suitable for analysis, relevant features are identified and extracted from the preprocessed data. These features are the basic indicators of student agency and are constructed using the psychometric model underlying the AUS scale. A technique from unsupervised machine learning, namely robust clustering, was used to create a representation of different experiences of agency. The results indicated that four profiles would provide a rich representation of the individual student agency experiences without being too general or too detailed (Jääskelä et al., 2021).

Figure 1. Visualization for the teacher showing the general average agency and four distinct profiles (Heilala, 2022)



The main outcome of the analysis is the visualization representing the general average student agency and the deviations of each of the four distinct profiles in terms of all the student agency profiles (Figure 1). The novel bars-in-bar visualization functions as a visual analytics tool for the teachers to reflect on their pedagogical decision-making (Cui, 2019; Heilala et al., 2022; Vieira et al., 2018). To facilitate transparency and interpretability of the results, the analysis also utilizes explainable artificial intelligence (XAI) to provide more fine-grained characterizations of the profiles (Saarela et al., 2021). For example, XAI provides insight into why a particular student was assigned to a specific agency profile (i.e., a local explanation) or how the detailed characteristics of a specific profile are constructed (i.e., a global explanation). In essence, XAI in student agency analytics opens a transparent window into the model's decision-making process, detailing the why and how behind its classifications. This helps to ensure that educators and students can understand and trust the insights provided by the analytics system, allowing for more informed and ethical educational decisions. XAI could function as an adaptive source (see, Martin et al., 2020) providing input for adaptive AI targeting learning and teaching processes (Figure 2).

Ethical considerations are vital in student agency analytics, especially when dealing with personal and potentially sensitive data. Key ethical issues identified in learning analytics encompass, for example, privacy, transparency, labeling, data ownership, algorithmic fairness, and the obligation to act (Tzimas & Demetriadis, 2021). The General Data Protection Regulation (GDPR) mandates privacy and transparency in data controlling and processing, with many students expressing concerns about data security, storage, and the transparency of analytics processes (e.g., Ifenthaler & Schumacher, 2016). While there are debates about data ownership, the student agency analytics process emphasizes privacy by using data aggregation, thus ensuring that individual results are only available to the respective students and teachers receive aggregated results that maintain student anonymity. Additionally, software architectural designs, like microservices, have been proposed to separate data controllers and processors, offering an added layer of privacy protection through pseudonymization (Ianculescu & Alexandru, 2020; Jääskelä et al., 2021).

In summary, student agency analytics, situated at the crossroads of educational research, computational psychometrics, and learning analytics, focuses on understanding and enhancing students' intentional learning and agentic resources. The approach quantifies student agency within different educational contexts, offering insights into individual learning experiences and more general group profiles suggesting prompts for pedagogical decision-making. The process is cyclical, starting with the teacher's initial planning, followed by student feedback through a psychometric measurement, and culminating in refined teaching strategies based on analytics. This data-driven approach employs the AUS scale to measure various dimensions of student agency, with robust clustering used to analyze diverse agency experiences. The results, visualized for educators, can be enhanced with explainable artificial intelligence (XAI) to ensure transparency in the model's decision-making. Ethical considerations, including privacy, transparency, and data ownership, are paramount, with actions like data aggregation and pseudonymization ensuring the protection of students' sensitive information.

3. CORE TECHNOLOGIES BEHIND STUDENT AGENCY ANALYTICS

This section deals with the underlying technologies used in developing student agency analytics. First, it briefly traces computational psychometrics, highlighting its synergy with learning analytics. Then, latent profile analysis using robust clustering is introduced as an essential technique for identifying distinct student agency profiles. The section concludes by spotlighting explainable artificial intelligence (XAI), underscoring its role in making machine learning models transparent and actionable within the domain of student agency.

3.1 Computational Psychometrics

Psychometrics is a field that studies measurement and modeling procedures—depending on epistemological stance—in educational and psychological contexts (Uher, 2021). The use of psychometric theories, concepts, and methods to analyze and quantify behavioral characteristics, cognitive functions, experiential qualities, and other latent factors relevant to learning processes is central to this field of study (e.g., Mislevy & Bolsinova, 2021; Thomas & Duffy, 2023). Learning analytics is suggested to benefit from the broad collection of research and methodological techniques provided by psychometric research within a broader interdisciplinary framework. In other words, whereas learning analytics is suggested to begin with multimodal data and technology, psychometrics begins with high-level interpretations and evidence-centered design (Drachsler & Goldhammer, 2020; Mislevy, 2019). Thus, the intersection of these domains provides an interesting approach to understanding and improving learning.

Computational psychometrics is "a blend of data science techniques, computer science, and principled psychometric approaches to aid the analyses of complex data as obtained from performance assessments and technology-enhanced learning and assessment systems" (von Davier et al., 2021, p. 2). The approach has been utilized in various studies and applications involving multimodal data and technology-enhanced environments. For example, Cipresso, 2015 introduced a three-step approach to study behavior dynamics in virtual reality using computational psychometrics, which showed that the virtual environment effectively elicited stress and behavioral responses. LaFlair et al., 2023 outlined how machine learning and psychometrics facilitate item generation for assessments and allow for the analysis of bigger, richer, and more diverse data, resulting in an improved test-taker experience. Hernandez et al., 2022 proposed an approach combining traditional situational judgment tests with gamification and machine learning to score and assess job candidates' soft skills. The study suggested that gamification coupled with psychometric modeling can be useful for improving the accuracy and effectiveness of employee behavior assessment. Poojitha et al., 2023 presented a machine learning framework for efficient assessment and prediction of human performance in a collaborative learning environment where computational psychometrics are used to model real behavior characteristics. The studies underscore the versatility and potential of computational psychometrics in diverse contexts, from virtual reality to employment assessments. Researchers can derive deeper insights and more accurate human behavior and performance models by integrating advanced data techniques with traditional psychometric principles.

In summary, building on the principles of psychometrics and its relation with learning analytics, computational psychometrics integrates with computer science and psychometric theories and methods. The integration allows for detailed analysis of multimodal data from various educational settings. From this intersection, latent profile analysis and explainable artificial intelligence emerged as key tools in developing student agency analytics.

3.2 Latent Profile Analysis

The eleven student agency dimensions in the three resource areas (see Figure 1) are formed via the pattern matrix, which has been determined using the confirmatory factor analysis (Jääskelä et al., 2020). This factor-based latent representation is then summarized to the whole student sample level to enable comparison of the agency of an individual student with the whole sample under study. The student agency knowledge discovery for teachers and educational administrators is based on the latent profile analysis (Grunschel et al., 2013), with four distinctive profiles (Jääskelä et al., 2021; Jääskelä et al., 2020).

Partitive clustering algorithms can be used to identify the subsets in a student sample with different agency profiles. Various methods and algorithms exist for this purpose (Estivill-Castro, 2002), among which methods based on robust statistics and the corresponding whole and subsample estimates are especially appealing (García-Escudero et al., 2010). Namely, statistical robustness refers to methods not excessively affected by outliers or deviations from the expected data patterns (Huber, 1981) and can, therefore, be used with small samples (Kärkkäinen & Heikkola, 2004). In other words, robust methods provide reliable estimates even when data comes from a class of only tens of students and may contain missing values, anomalies, and non-Gaussian error distributions. The latter happens when the original data from the AUS questionnaire is of Likert-scale.

In summary, robust clustering is a stable and reliable technique for discerning different latent profiles of students based on their individual experiences of student agency. The technique identifies distinct student groups with shared characteristics and experiences (Jääskelä et al., 2021). The principles of robust clustering could be extended to various educational settings where psychometric measurements from a Likert-scale questionnaire are employed, offering a convenient method to discern unique learner profiles based on diverse data. However, while robust clustering offers valuable insights into student profiles, there is an increasing demand for transparency in these methods, highlighting the need to employ explainable approaches.

3.3 Explainable Artificial Intelligence (XAI)

XAI seeks to demystify the often complex and opaque algorithms of AI, making their inner workings more understandable to humans. The concept, although gaining recent attention, has historical roots, such as the medical recommendation system introduced by Shortliffe et al., 1975, which provided interpretable results to physicians. XAI emphasizes understandability, transparency, interpretability, and explainability, countering the ”black box” nature of many AI models (Angelov et al., 2021). It is pivotal in deciphering complex machine learning models and making their decisions transparent, thus establishing appropriate trust in and effectively overseeing the outcomes produced by AI (Adadi & Berrada, 2018; Barredo Arrieta et al., 2020).

When we refer to the need for an explanation regarding a decision, we generally imply the requirement for reasons or rationales behind a specific result rather than an account of the internal mechanisms or the overall logical process guiding the decision-making procedure. Utilizing XAI systems furnishes the necessary information to substantiate results, particularly when unexpected determinations arise. Furthermore, it establishes a trackable and verifiable approach to defending algorithmic choices as equitable and morally sound, fostering the cultivation of trust. The significance of explainability transcends mere justification of decisions; it also plays a preventive role. Indeed, gaining a deeper understanding of system behavior enhances visibility into previously unidentified susceptibilities and imperfections, enabling the swift identification and rectification of errors in less critical situations (debugging). This, in turn, empowers a heightened level of control.

Most XAI techniques focus on feature relevance to explain AI and machine learning models (Saarela & Jauhiainen, 2021). Various of these methods, like SHapley Additive exPlanation (SHAP) (Shapley, 1953) and local interpretable model-agnostic explanations (LIME) (Lundberg & Lee, 2017), are post-hoc, meaning they are applied after the AI model has been trained to shed light on the model's decision-making processes. Additionally, some machine learning algorithms, like random forests (Breiman, 2001), inherently offer a degree of transparency, allowing the quantification of feature relevance. Regarding the explanation space, both—posthoc and intrinsic—explanation methods can be classified into local versus global interpretability. Global interpretability involves comprehending the overarching decision-making process of a model, while local interpretability centers around elucidating explanations for individual predictions.

Utilizing XAI in student agency analytics allows for a deeper understanding of how specific dimensions contribute to different educational experiences regarding agency profiles. This transparency is crucial for learners, educators, and stakeholders, as it provides actionable insights into the factors that enhance or hinder student agency. Saarela et al. (2021) proposed that the purpose of integrating XAI techniques with the student agency analytics process is to support the transparency and data-based development of automated feedback systems in education and to advance teachers' pedagogical awareness and reflection by providing actionable information on students' learning efforts in relation to their perceived agentic affordances. Overall, their study suggested that incorporating XAI into practice could support the development of automated feedback systems and increase pedagogical knowledge. In addition to XAI techniques, furture studies using clustering could also examine how explainable clustering could contribute to transparency. Explainable clustering (Moshkovitz et al., 2020) utilizes decision trees to characterize k-means and k-median cluster assignments, aiming at optimal pre-modeling explanations for given clusterings and the computational complexity influenced by various parameters (Bandyapadhyay et al., 2023).

In summary, XAI techniques aim to enhance the transparency and comprehensibility of complex AI algorithms. In addition to providing clarification on decisions made, the techniques could contribute to the improvement of the AI system and the identification of errors and biases. Methods such as SHAP, LIME, and transparent algorithms like random forests provide valuable insights into the decision-making mechanisms of AI. The integration of XAI in the field of education could provide benefits by providing useful insights into student agency, improving feedback systems, and expanding instructional expertise. Furthermore, emerging methodologies such as explainable clustering demonstrate the possibility of achieving enhanced transparency.

4. TOWARD ADAPTIVE LEARNING AND TEACHING

This section provides insight into how adaptive AI can be utilized in education by taking examples from the domains of serious games and pedagogical agents. These AI solutions can provide personalized learning experiences, boosting user involvement and facilitating learning processes. However, while there are potential educational benefits, it's crucial to approach their integration by considering ethical implications, user expectations, and the importance of transparency in decision-making processes.

4.1 Adaptive AI in Education

Adaptive AI refers to artificial intelligence systems that can modify their behavior over time based on the data they process, the feedback they receive, and the available resources (Gartner, 2022; Shen et al., 2021). In other words, instead of being static in their modeling, adaptive AI systems learn from new information and adjust their actions or predictions accordingly (e.g., Kumar & Kumar, 2018; Penttilä et al., 2019). In education, adaptive AI systems are expected to adjust and personalize educational content and experiences based on individual student needs, preferences, and performance (e.g., Younes, 2021). The primary goal is to provide a more tailored educational experience, for example, by ensuring that students receive the right content at the right pace, thereby enhancing learning processes.

Serious games have the potential to benefit from adaptive AI to enhance user experience, tailor content to individual learning approaches, and provide real-time feedback, thereby making the gaming environment more engaging and effective for educational and training purposes (Aydin et al., 2023; Niemelä et al., 2020). According to Mansouri et al. (2021), the utilization of adaptive AI can augment player engagement with serious games by customizing the gaming experience to align with each player's unique requirements and preferences. This can be accomplished by analyzing the player's behavior and subsequent modification of the game's mechanics, level of difficulty, and content appropriately. By implementing this approach, the game shows an increased degree of challenge and reward, hence potentially fostering higher levels of motivation and engagement. For example, Fraser et al. (2018) found that user engagement can be supported by emotion detection and emotional dialogue management to enhance the conversational experience in video games.

Pedagogical agents are computer-generated characters designed to support learning by interacting with students human-likely and providing feedback, answering questions, and guiding students through learning activities (Sikström et al., 2022). In their research, Hauptman et al. (2023) provided recommendations and insights into the design and implementation of AI teammates in various educational team situations, such as cyber incident response, data science, and computer security. They defined autonomous teammates as artificial agents that can function independently and make decisions without the need for human intervention. These adaptive autonomous agents are designed to adjust their level of autonomy based on the team's needs and the situation. The research provided design recommendations for enhancing human-AI team dynamics and the design of AI teammates with adaptive autonomy. Firstly, it emphasized the importance of work cycles in determining the level of autonomy of AI teammates. AI agents should dynamically adapt their autonomy based on predefined points in teamwork cycles, similar to how less experienced team members would. This dynamic adaptation should feel natural, avoiding manual adjustments that can disrupt team performance and focus. Over time, AI could even predict changes in the team's work cycle for better adaptation. Secondly, AI teammates should have higher autonomy during well-defined, predictable team processes. For instance, in phases requiring more straightforward decisions and actions, AI agents should have more autonomy but less during phases that require more human reasoning. Lastly, a training mode should be introduced to address initial concerns about AI teammates. This mode would allow team members to manually control the AI's adaptation manually, aiding in familiarization.

Li and Gu (2023) proposed a risk framework for human-centered artificial intelligence (HCAI) that primarily seeks to manage risks methodically and assist stakeholders in maximizing benefits through proactive measures. The framework is designed to promote responsible, sustainable, and human-centric AIED, and it was developed through a literature meta-analysis and a Delphi process to pinpoint eight pivotal risk indicators. The risk indicators in the framework are a misunderstanding of the HCAI concept (MC), misuse of AI resources (MR), mismatching of AI pedagogy (MP), privacy security risk (PSR), transparency risk (TR), accountability risk (AR), bias risk (BR), and perceived risk (PR). The indicators are systematically categorized into four distinct areas. Firstly, the HCAI Concept category solely comprises the risk of misunderstanding the HCAI concept. Secondly, the Application Process category addresses risks associated with the misuse of AI resources and the mismatching of AI pedagogy. Thirdly, the Ethical Security category concerns risks relating to privacy and security, transparency, accountability, and bias. According to the authors, these risks are particularly concerning as they emerge from overlooking the inherent values of AI technology, which could potentially clash with the foundational objectives of education. Lastly, the Man-Machine Interaction category consists of the perceived risk indicator, which is rooted in the ethical dilemmas posed by the misuse of AI technology in education governance. The authors utilized the Delphi method to find out the ranking of the risk indicators, which was described as MP > MR > AR > PSR > TR > PR > BR > MC. The result indicated that the mismatching of AI pedagogy, misuse of AI resources, and accountability risk were some of the main concerns among experts in the Delphi panel. In addition to potential risks, the effectiveness of adaptive AI systems in education should be considered with care. For example, Kosch et al. (2023) reported an interesting finding that suggested that descriptions of technical systems can elicit placebo effects through user expectations, biasing the results of user-centered studies. Their study found that the belief of receiving adaptive AI support increases expectations regarding the person's own task performance. Overall, the study highlights the importance of considering user expectations and placebo effects in evaluating AI-based user interfaces and novel AI systems in education.

From an ethical perspective, XAI is suggested as a promising approach when dealing with adaptive AI in education. As adaptive AI systems augment educational processes based on multimodal data, it's essential for stakeholders to understand how these systems make decisions to tailor these processes. This transparency is vital for making informed and fair educational decisions. Khosravi et al. (2022) discussed the importance of transparency and accountability in AI systems used in education and how XAI can help increase trust in these systems. The authors present the XAI-ED framework, which consists of five components: i) stakeholders and potential benefits, ii) approaches for presenting explanations, iii) used classes of AI models, iv) human-centered designs of the XAI interfaces, and v) potential pitfalls of providing explanations and how to avoid them. The framework aims to provide a structured approach to designing and evaluating XAI systems in education. The stakeholder aspect considers the different groups of people who are involved in the educational process and how they may benefit from XAI. The benefits aspect examines the potential advantages of using XAI in education, such as increased transparency and accountability. The explanations aspect looks at different methods for presenting explanations to users, such as visualizations or natural language explanations. The AI models aspect considers the different types of AI models that are commonly used in AIED, such as decision trees or neural networks. The human-centered design aspect focuses on designing AI interfaces that are user-friendly and easy to understand. Finally, the potential pitfalls aspect examines the potential challenges and limitations of implementing XAI in educational settings, such as the complexity of educational data or the need for domain-specific knowledge.

In summary, adaptive AI could transform education toward adaptive learning and teaching by delivering personalized learning experiences that cater to each student's unique needs. Its potential impact is already noted in areas like serious games, which use AI to boost user engagement through personalized content and pedagogical agents that provide human-like interactions and feedback. However, while the advantages are potentially significant, it is imperative to integrate adaptive AI thoughtfully, considering the potential risks, user expectations, and the critical importance of transparency.

4.2 From Adaptive AI to Adaptive Learning and Teaching

Adaptive learning can be considered both as a technology and a process that is suggested to have benefits for learning: using technologies like machine learning and virtual learning environments, it actively modifies the delivery of educational content according to a student's understanding of the subject, as determined by their reactions to assessments or their specific learning preferences (Essa et al., 2023; Martin et al., 2020). Generally, a process refers to a series of steps to reach a particular objective. In this context, the process perspective of adaptive learning focuses on how to attain the objective (e.g., learning outcome) using adaptive AI, while the technology perspective centers on adaptive AI, highlighting the technology behind the design and building of artifacts used in adaptive learning (e.g., adaptive pedagogical agents) called as adaptive learning systems in general. In other words, in the context of student agency analytics, adaptive learning refers to learning processes utilizing adaptive AI as technology that could be integrated into an artifact forming an adaptive learning system. From the ANT point of view, these processes and artifacts are not isolated but are deeply intertwined with various actors in a wider context. These actors can include not only humans like educators, learners, peers, and administrative personnel but also non-human actors such as other algorithms, software systems, and adaptive learning tools utilizing various technologies.

However, artificial intelligence in education does not automatically support personalized learning. Ouyang and Jiao (2021) proposed three paradigms of artificial intelligence in education, namely, AI-directed (i.e., learner-as-recipient), AI-supported (i.e., learner-as-collaborator), and AI-empowered (i.e., learner-as-leader). AI systems steer the learning process in the AI-directed paradigm, placing learners as passive knowledge recipients. Conversely, the AI-supported paradigm considers learners actively collaborating with AI, offering guidance throughout the learning paths. Lastly, the AI-empowered paradigm emphasizes learner agency, treating AI systems as tools to enhance human characteristics, drawing from the complexity theory that perceives education and learning as a complex adaptive system (e.g., Chiva et al., 2008; Jörg et al., 2007), necessitating collaboration among its various components. Within these paradigms, adaptive AI is best situated within the AI-empowered paradigm. Here, adaptive learning tailors content based on individual learner needs and empowers learners to take charge of their educational journey.

Martin et al. (2020) proposed in their literature review an adaptive learning framework that applies elements from both Shute and Towle (2003) and Vandewaetere et al. (2011), integrating components like the learner model, content model, instructional model, and an adaptive engine, with the latter utilizing AI to individualize learning pathways based on user feedback and learner profiles. The review identified that learner modeling utilized various adaptive sources, encompassing learners' attributes, knowledge, proficiency, behavior, preferences, and individual differences. These various learner characteristics used in modeling included log data, different psychometric instruments (e.g., learning style), and variables like time spent on a task and proficiency level. The review found that adaptive learning applications focused on content, assessment, presentation, and navigation, with research emphasizing adaptive feedback based on student understanding of concepts and reasoning, navigation tailored to individual learning paths, and content presentation in varied formats and modalities. The authors suggested that future research in adaptive learning should focus on qualitative methods to understand the mechanisms behind the positive impacts of adaptivity, employ experimental designs and meta-analyses to identify causal patterns and their effects, and examine the specific adaptive strategies and technologies used.

Adaptive teaching, on the other hand, focuses on inclusive teaching practices and involves educators drawing on their expertise to create versatile learning situations with the goal of maintaining the majority of students in this "middle ground" that "brings students at different levels closer together" (Corno, 2008, p. 166). This approach leverages the diverse abilities within the class, encourages students to exchange insights and fosters skill development. According to Gallagher et al., 2022, adaptive teaching is a dynamic pedagogical approach where teachers spontaneously modify their instruction to cater to their student's diverse needs. They suggest that by recognizing students' varied learning approaches and abilities, adaptive teaching emphasizes continuous pedagogical adjustments based on classroom observations, such as unexpected student inputs or misconceptions. Based on a literature review, they found that the key areas of teacher expertise contributing to adaptive teaching are 1) noticing the aspect to which the teacher must attend, 2) teacher reflection and metacognition, and 3) teacher's action. Gallagher et al., 2022 emphasized that professional noticing is a critical component of adaptive teaching involving a teacher's ability to observe and interpret classroom situations and to use this information to make informed decisions about their instruction. They suggest that teachers who can notice and respond to student thinking are more effective at promoting student learning than those who are not.

Professional noticing, a key skill underpinning all professional practice, is the ability to observe and interpret situations and events in a work setting and to use this understanding to inform decisions and actions (Rooney & Boud, 2019). According to Gibson and Ross (2016), the teacher's professional noticing involves various features, such as engaging in thorough hypothesizing, providing detailed elaboration, identifying learners' metacognitive processes, and identifying important moments. The authors suggest that it is crucial for teachers to accurately understand and interpret students' responses in order to make informed decisions on instructional strategies and provide relevant support. In other words, through professional noticing, teachers can accurately identify their students' strengths and weaknesses, enabling them to customize their instructional methods accordingly. The results of their study highlight the importance of professional noticing in promoting adaptive teaching practices, improving pedagogical skills, and providing continuous development for teachers through their own ability to adapt. In general, professional noticing serves as a fundamental aspect of adaptive teaching, enabling teachers to provide personalized instruction that aligns with the specific needs of their students.

H. Park and Zhang (2022) examined how analyzing students' temporal progress and participation in a visual online platform for collaborative knowledge building facilitated teachers' noticing. They found that the main advantage of the technology and analytics was presenting teachers with an overview of students' evolving thought processes, highlighting students' valuable insights regarding central concepts within the collaborative platform. The results indicated that with analytical feedback, teachers were better positioned to recognize and value students' deep and promising ideas that might have gone unnoticed otherwise.

Kärner et al. (2021) introduced a Teachers' Diagnostic Support System (TDSS), a prototype of a task-specific decision support system utilizing learning analytics to support teachers' daily diagnostic tasks and micro-adaptive strategies. The TDSS collected data on students' personal attributes, such as domain-specific knowledge and emotional-motivational traits. It also gathered information on instructional characteristics like the nature of the learning content and tracked students' learning experiences and progress, including their interests and knowledge about a topic. Analytically, the TDSS examined variations between students, like differing prior knowledge. It also analyzed changes within individual students over time, variations in teaching methods, and the interplay between students' knowledge levels and task challenges.

According to Standen et al. (2020), adaptive learning systems can enhance adaptive teaching by using AI to understand students' emotional states better and tailor teaching methods accordingly. They concluded that notable applications include optimizing communication strategies for autistic students and providing real-time feedback on student engagement with materials. However, they also emphasized that these systems often face challenges, including limited practical testing and the absence of standardized evaluation criteria. Furthermore, many educators do not fully grasp how the technologies function.

In summary, adaptive learning, which merges technology and pedagogical processes, adjusts educational content and instruction based on student performance. This is primarily achieved through AI systems, which can be either directive, supportive, or empowering. For truly individualized learning experiences, an empowered approach would be ideal, letting learners assume agency in their learning pathways. Adaptive teaching focuses on educators' ability to respond to diverse student needs. Central to this concept is professional noticing, which helps educators observe and make informed pedagogical decisions.

5. INTEGRATING STUDENT AGENCY ANALYTICS WITH CONCEPTS IN ADAPTIVE AI

This section explores the potential and tentative approaches to how adaptive AI may utilize student agency analytics to improve various outcomes. The section suggests ways to contribute to student-centered teaching and learning through agency-aware adaptive AI. However, responsible application of these approaches requires understanding ethical considerations.

5.1 Potential Applications

Through the lens of student agency analytics, adaptive AI has the potential to support how educators approach student-centered teaching and how students engage with their learning. By understanding and leveraging the elaborate interplay between student agency and adaptive AI, educators and technologists could co-create learning environments that are both technologically advanced and student-centric. The following suggests how student agency analytics could potentially be harnessed to produce relevant input features and prompts for AI models, improve modeling accuracy, evaluate the effectiveness of adaptive AI systems, augment teaching practices, and advance the AI-empowered learning paradigm.

5.1.1 Feature Engineering

Relevant input features are crucial for the performance and accuracy of AI models, as they directly influence the model's ability to discern patterns and make predictions (Linja et al., 2023; Verdonck et al., 2021). Feature engineering, the process of selecting, transforming, and creating the most informative features, plays a key role in enhancing the model's functioning (e.g., Kuhn & Johnson, 2019). Without valid feature engineering, even the most sophisticated AI algorithms can produce misleading results or fail to capture the underlying relationships in the data. By leveraging psychometric principles, feature selection and engineering can be more targeted, ensuring that AI models are informed by variables that genuinely reflect students' cognitive abilities, behaviors, and experiences. For example, Zehner et al. (2021) used a ”top-down approach for engineering features by means of psychometric modeling“ to estimate students' test-taking speed and ability and then extracted features from log data and derived simple indicators to improve machine learning for predictive classification tasks. The top-down approach aligns with the notion of how psychometrics first considers high-level interpretations (Drachsler & Goldhammer, 2020; Mislevy, 2019). By discerning the multifaceted dimensions of a student's learning experience, student agency analytics offers a rich set of input features for adaptive AI systems. These features capture nuanced aspects of a student's learning experience, such as self-efficacy, competence beliefs, interest, and reliance on peer support. When integrated into adaptive AI systems, these data points enable the AI model to personalize, for example, content, feedback mechanisms, and collaborative learning environments to the needs and preferences of each student. By understanding a student's agency profile, the AI model could predict potential challenges, optimize learning paths, and provide timely interventions. Thus, student agency analytics could act as a bridge, translating intricate human learning experiences into actionable data for AI-driven personalization.

5.1.2 Prompt Engineering

With the advent of large language models (LLMs), prompt-based learning has emerged as an effective paradigm for conducting predictive natural language processing (NLP) tasks (Liu et al., 2023). A prompt is a directive given to an LLM to tailor or improve its functions, and prompt engineering is the process of optimizing these directives by exploiting the established prompt patterns (e.g., White et al., 2023). There have been some recent attempts to use LLMs to examine personality traits and automatically generate measurement items. For example, Safdari et al. (2023) claimed that LLMs could reliably and validly simulate personality and create outputs that reflect specific personality profiles. Laverghetta and Licato (2023) utilized an LLM and a prompting strategy for automated item generation (AIG) of psychometric test items. Computational psychometrics like student agency analytics could provide insightful frameworks for composing prompts that capture and reflect the intricate nuances of student behaviors, motivations, and learning experiences. Integrating LLMs, prompt engineering, and computational psychometrics could lead to a more nuanced interaction between users and LLMs, where the model's responses are both linguistically accurate and aligned with the educational and psychological dimensions of the learner.

5.1.3 Improving Model Accuracy

Self-reported measures in education are tools where students provide information about themselves without external verification. They may be subject to biases, as responses are based on personal perceptions and might not always represent objective reality (e.g., Jia et al., 2023). However, in learning analytics, the integration of self-reported measures has been suggested to be a useful approach, offering a more comprehensive view of students' learning experiences and enhancing the predictive power of the data. For example, Ellis et al. (2017) employed a questionnaire to gather self-report data on students' learning approaches and paired this with observational data from an online learning environment. The objective was to predict academic performance. By merging self-report and observational data, three independent variables were identified that significantly predicted students' academic performance: the surface approach to study, the frequency of accessing an online resource, and the number of multiple-choice questions answered. This combination approach underscores the value of self-report measures, suggesting they can enhance analysis by offering a richer understanding of students' learning experiences. Tempelaar et al. (2020) acknowledged the biases of self-reported measures but argued that the measures can still be valuable in predicting academic performance. Interestingly, their study posited that these biases could even add predictive power when explaining performance data and self-reported data. This perspective challenges the traditional view of biases as purely detrimental, suggesting that self-reported measures can, in certain contexts, provide deeper insights into student learning and performance. Ifenthaler et al. (2023) explored the alignment between self-reported data on self-testing procedures and behavioral data sourced from learning analytics systems. Their study proposed that merging self-report data with trace data, especially when investigating how learners engage with resources, yields more accurate results. The combined approach offers a more holistic view of student engagement and serves as a validation tool for analytics results. Also, beyond predictive analytics, self-reported measures have implications for intervention and feedback systems based on learning analytics. Dawson et al. (2017) emphasized the importance of considering students' individual characteristics, such as self-efficacy and prior studies, when designing these systems. Self-reports emerge as a potent tool in this context, helping identify individual aspects and factors, like a student's expected grade. Recognizing these individual nuances can significantly impact students' learning behaviors. More importantly, it can pave the way for more personalized feedback, tailored to address specific student needs and preferences. Based on the findings above, student agency analytics could offer a more nuanced and comprehensive understanding of student learning experiences and, thus, improve model accuracy in adaptive learning systems.

5.1.4 Evaluating Effectiveness of Adaptive AI

The effectiveness of AI in education should be examined across multiple domains, cultural contexts, and practical settings (Pinkwart, 2016). Also, learning perceptions as an outcome have received less attention than learning achievements in studies dealing with the effectiveness of AI in education (Zheng et al., 2021). Most notably, AI in education should foster student agency rather than undermine it (Nguyen et al., 2023; Ouyang & Jiao, 2021). Therefore, if one is committed to a humanistic and student-centered view of education, student agency as a construct offers a theory-driven lens to evaluate students' learning perceptions in different learning situations applying AI systems. In other words, student agency analytics could provide useful metrics to evaluate the effectiveness of adaptive AI systems in education. When students interact with adaptive AI systems, the degree to which they feel empowered, autonomous, and capable of influencing their learning trajectory can be assumed to have an association with the system's adaptability. If an adaptive AI system effectively tailors learning experiences, students should exhibit heightened agency, as the system would be personalizing content, feedback, and other resources to their individual needs and preferences, thereby fostering a more student-centered learning environment. By monitoring changes in student agency before and after the introduction of an adaptive AI system, researchers and educators could assess the system's impact. A significant increase in student agency would suggest that the AI system is effectively recognizing and responding to individual student needs in terms of agency, while stagnant or decreasing levels might indicate a need for further refinement of the system.

5.1.5 Augmented Teaching

Student agency analytics employs visual analytics to present a clear and concise representation of the learning experience, enabling teachers to gain insights and make informed decisions about their teaching practices. The visual representation can help teachers to narrow down their attentional space and focus on specific areas that require intervention or enhancement. In other words, visual analytics can facilitate teachers' situation awareness (Y. Park & Jo, 2019) and professional noticing (H. Park & Zhang, 2022). As a result, teachers could respond more effectively to individual student needs, fostering a micro-adaptive (Corno, 2008) learning environment that is inclusive, responsive, and dynamic. Furthermore, the underlying educational framework of student agency can facilitate teachers' reflection and meta-cognition (Heilala et al., 2022). Consequently, teachers can engage in a continuous cycle of reflection, adaptation, and improvement. The approach can be considered an example of augmented teaching, which combines the teacher's professional expertise with technological capabilities to enhance pedagogical decision-making and actions. Lastly, professional noticing is a capability that can be deliberately practiced (Rooney & Boud, 2019), and student agency analytics could be used as a learning tool in teacher education, augmenting the teaching of pre-service teachers.

Advancing AI-empowered learning by providing students with access to their own visualized student agency data, they can take a more active role in their learning journey. This democratization of data allows students to self-reflect on their learning practices, strengths, and areas of improvement. Students gain opportunities to engage in meaningful dialogues with their teachers, co-creating personalized learning strategies. Also, other adaptive learning systems can utilize student agency analytics data to adapt their own internal algorithms. For example, a collaborative learning platform could utilize dynamic grouping based on students' competence and self-efficacy experiences or provide students with prompts based on peer support levels. The approaches above can potentially advance the AI-empowered learning paradigm (Ouyang & Jiao, 2021) by transforming AI systems in education from mere instructional tools to enablers of student-centered and meaningful learning.

5.2 Ethical Perspectives

When applying student agency analytics to enhance personalized learning paths, XAI can help ensure that the adaptability of AI is both transparent and aligned with individual student characteristics (Saarela et al., 2021). By offering insights into adaptive AI processes, XAI methods could help researchers, developers, and practitioners ensure that the dynamic learning adjustments suggested by AI are both comprehensible and beneficial to the student's educational trajectory. The XAI-ED (Khosravi et al., 2022) and HCAI (Li & Gu, 2023) frameworks can be used to outline the different ethical perspectives of student agency analytics.

Considering the stakeholders and potential benefits through the lens of the XAI-ED framework, student agency analytics offers distinct advantages for educators, students, educational researchers, and policymakers. Educators can gain actionable insights for refined pedagogical decisions, while students could receive a reflective view of their learning pathways, potentially promoting autonomy and agentic learning. Educational researchers could benefit from a rich set of features that can inform more comprehensive studies on learning behaviors and outcomes, and policymakers could use research-based insights to craft informed educational strategies and guidelines for student-centered learning. From the human-centered AI perspective, the HCAI framework emphasizes the need for AI tools in education to be designed with responsibility and sustainability at the forefront (Li & Gu, 2023). Student agency analytics aims not only to deliver data-driven insights but also to do so in a form that is transparent, interpretable, and centered on the diverse needs of different educational stakeholders. Relating to approaches for presenting explanations, student agency analytics aims to translate intricate psychometric data into comprehensible insights by using visual analytics. The visualization technique aligns with the HCAI framework, which underscores the importance of designing AI solutions that are both interpretable from the educational point of view and aligned with pedagogical approaches. In other words, the approach emphasizes the importance of balancing innovative AI applications in education with the need to avoid the mismatching of AI pedagogy, ensuring that AI-driven insights remain relevant and user-centric. Concerning the used classes of AI models, student agency analytics utilizes advanced techniques such as computational psychometrics, robust clustering, and XAI to clarify multidimensional learning experiences. The incorporation of SHAP (Shapley, 1953) and LIME (Lundberg & Lee, 2017), with their focus on model interpretability, aims to facilitate the human-centric design for the XAI interface, underscoring the importance of the dimensions of ethical security. However, while these techniques can potentially offer transparent insights, stakeholders might question the validity or interpretability of AI-driven outcomes in real-world educational settings, depending, for example, on the perceived risk and the misunderstanding of the relevant concepts.

Finally, it's crucial to be aware of potential challenges. For instance, placing too much trust in automated results and explanations could unintentionally reduce the significance of an educator's contribution to pedagogical decisions. Additionally, the clarity brought about by these explanations might unintentionally reveal confidential student information or amplify intrinsic biases in the AI system. Given the multidimensional nature of student agency, there is also a possibility that the system's explanations might be too complex, making it challenging for educators or students to understand, which could result in misunderstandings. Thus, integrating human expertise with AI-derived knowledge and crafting explanations that align with the user's knowledge level is vital to address these issues. Furthermore, strong privacy safeguards need to be in place, and the AI models should undergo regular reviews to detect and correct any inherent biases.

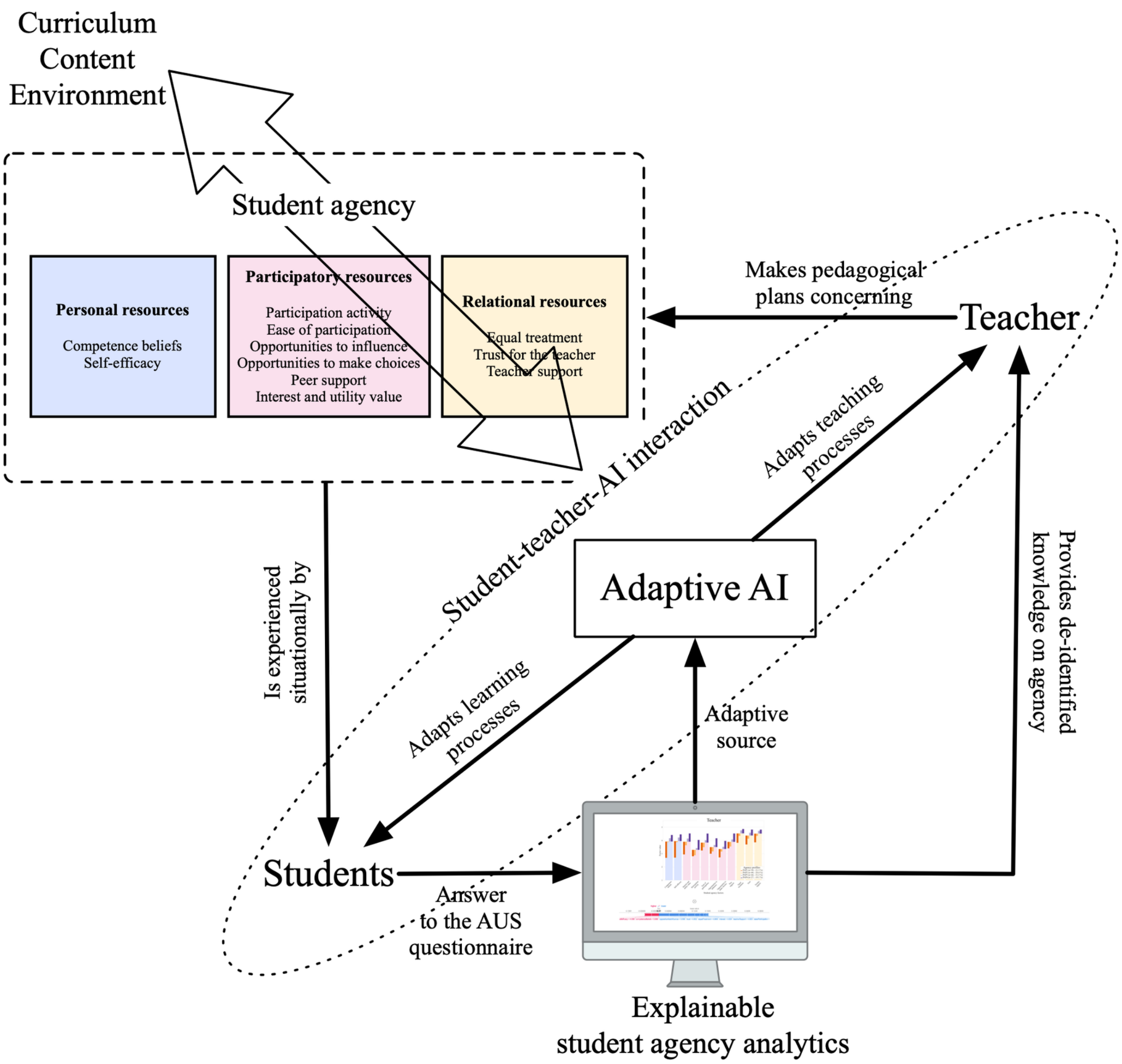
In summary, student agency analytics could support a transparent and tailored approach to enhancing personalized learning paths when integrated with XAI. Considering the analytics through XAI-ED and HCAI frameworks, the approach can deliver valuable insights for various educational stakeholders, from learners to policymakers. However, while the potential benefits are significant, addressing challenges such as over-reliance on analytics, potential exposure of sensitive data, and the complexity of provided insights, emphasizing the importance of human expertise, user-tailored explanations, and continuous model evaluations is essential.

6. CONCLUSION

With the digital transformation that has been ongoing globally, there has been a growing recognition among educational institutions of the imperative to harness data for refining educational processes and outcomes (Banihashem et al., 2022; Mukul & Buÿüközkan, 2023). At the same time, the concept of student agency has emerged as a crucial element in shaping purposeful and influential learning experiences in higher education (e.g., OECD, 2019; Stenalt & Lassesen, 2021; Vaughn, 2020). Recent studies briefly reviewed in this chapter have highlighted the profound connections between student agency and various educational results, emphasizing its significance, for example, in pedagogical decision-making and overall student satisfaction. This chapter considered the potential of adaptive AI in higher education, particularly focusing on the interplay between student agency and educational processes. By combining learning analytics with the research on student agency, a novel approach termed student agency analytics (Heilala, 2022; Jääskelä et al., 2021) was briefly introduced as an example application, offering a data-driven perspective to discern students' learning experiences. This synergy between adaptive AI and student agency analytics was suggested to hold promise for crafting more tailored and impactful educational experiences where student-teacher-AI interactions intertwine with curriculum, content, and environment (Figure 2).

Human agency, deeply rooted in philosophical traditions, encompasses the capacity for intentional action and change, influenced by individual intentions and broader social contexts (Schlosser, 2015). Within the educational realm, student agency emerges as a specialized facet of this broader concept, emphasizing students' ability to navigate, influence, and shape their learning experiences (Stenalt & Lassesen, 2021). In this chapter, the concept of student agency was used to refer to students' capacity to take control of their learning through various resources. In formal educational context, this capacity building interacts with the curriculum, pedagogical approaches and teaching practices, and the broader educational environment (Jääskelä et al., 2020; Jääskelä et al., 2023). Student agency analytics was

Figure 2. Adaptive student agency analytics as a cyclical process utilizing computational psychometrics (evolved from Saarela et al., 2021)



utilized to quantify and analyze this agency within educational settings. By leveraging computational psychometrics, robust machine learning, and data visualization, this approach provided insights into how students exercise their agency, offering educators a more comprehensive understanding of students' learning experiences (Heilala et al., 2022). The datadriven perspective, grounded in ethical considerations (Saarela et al., 2021; Tzimas & Demetriadis, 2021), aims to foster more intentional and meaningful learning experiences for students.

The core technologies underpinning student agency analytics are rooted in computational psychometrics, robust clustering, and explainable artificial intelligence (XAI). Computational psychometrics, a fusion of data science, computer science, and traditional psychometric principles, offers a comprehensive approach to analyzing complex data from educational settings (von Davier et al., 2021). Robust clustering, a variant of the k-means clustering technique, identifies distinct student agency profiles, emphasizing resistance to outliers and anomalies in the data (Jääskelä et al., 2021). XAI, on the other hand, aims to make the intricate algorithms of AI transparent and understandable. By demystifying the ”black box” nature of many AI models, XAI provides clear insights into the decision-making processes of machine learning models, ensuring trustworthiness and accountability (Angelov et al., 2021; Saarela et al., 2021). Integrating these technologies in student agency analytics offers a holistic understanding of students' learning experiences, potentially providing actionable insights for educators and stakeholders. Extending beyond student agency, the techniques of student agency analytics have the potential to enrich the analysis of other educational constructs. By harnessing computational psychometrics, robust clustering, and XAI, different professionals in education could delve deeper into concepts like student motivation, engagement, or collaborative learning dynamics. Similar holistic approaches, which are adaptable and scalable, could pave the way for more personalized educational interventions and a richer understanding of diverse learning experiences across various educational settings, leading to adaptive learning and teaching.

Adaptive learning, both a technology and a process, uses AI to modify educational experiences based on a student's performance and preferences (e.g., Essa et al., 2023; Martin et al., 2020). This ensures, for example, that learners receive content tailored to their learning pace and knowledge level, enhancing the overall learning process. Serious games, for instance, can employ adaptive AI to boost user engagement by personalizing content (Aydin et al., 2023), while pedagogical agents can interact with students in a human-like manner, offering feedback and guidance (Sikström et al., 2022). On the other hand, adaptive teaching focuses on educators using their expertise to create dynamic learning environments. For example, teachers adjust their instruction spontaneously based on classroom observations, such as unexpected student inputs or misconceptions (Gallagher et al., 2022). A critical skill underpinning adaptive teaching is professional noticing, which involves a teacher's ability to observe, interpret, and act based on classroom situations (Gibson & Ross, 2016; Rooney & Boud, 2019). Student agency analytics can play a pivotal role in teachers' professional noticing by enabling educators to discern and respond to individual student needs, preferences, and behaviors. However, while the potential benefits of adaptive learning and teaching are significant, it is essential to integrate these approaches thoughtfully. Ethical considerations, like user expectations (e.g., Kosch et al., 2023) and the importance of transparency in decision-making processes must be at the forefront (e.g., Khosravi et al., 2022; Saarela et al., 2021). In essence, adaptive learning and teaching promise a more individualized and effective educational journey, but their implementation requires careful consideration and continuous evaluation.

This chapter suggested a promising potential for augmenting student-centered teaching and learning by integrating student agency analytics with adaptive AI. By harnessing the power of student agency analytics, AI models could be fed with relevant input features, capturing the nuanced aspects of a student's learning experience, such as self-efficacy, peer support, and participation activity. As the recent research reviewed in this chapter suggested, self-reported measures and observational data combined could produce more accurate results (e.g., Dawson et al., 2017; Ellis et al., 2017; Ifenthaler et al., 2023; Jia et al., 2023; Tempelaar et al., 2020). The integration could enable a more comprehensive knowledge of students' learning experiences and possibly improve the accuracy of adaptive AI models. Furthermore, student agency analytics might provide a theorydriven lens to evaluate the effectiveness of adaptive AI systems. From the teachers' perspective, they can benefit from visual analytics, enabling them to make informed decisions and adapt their teaching practices responsively. This approach, augmented teaching, merges professional expertise with technological capabilities, enhancing pedagogical decision-making. The advent of LLMs offers an exciting avenue for enhancing the capabilities of adaptive AI in the educational realm. The synergy between LLMs, prompt engineering, and student agency analytics could lead to more personalized and context-aware AI interventions, further amplifying the benefits of student-centered learning. Lastly, democratizing data by giving students access to their visualized agency data empowers them to actively participate in their learning journey actively, fostering meaningful dialogues and co-creating personalized learning strategies. In essence, the fusion of student agency with adaptive AI has the potential to transform AI systems from mere instructional tools to catalysts for studentcentered, meaningful learning.

6.1 Future Directions

Exploring student agency analytics, adaptive learning, and adaptive teaching discussed in this chapter opens several avenues for future research. One of the most promising directions lies at the intersection of computational psychometrics and learning analytics. As these domains continue to merge (e.g., Drachsler & Goldhammer, 2020), there is potential for developing more sophisticated models that can assess learning outcomes. Future studies could consider how multimodal data, combined with psychometric models, could offer richer insights into student agency, especially in online and hybrid learning environments. Latent profiling using robust clustering, having demonstrated its efficacy in identifying distinct student agency profiles in higher education (Jääskelä et al., 2021), can be utilized in other educational contexts. Future research could explore its application in different educational settings, cultures, and age groups to understand how student agency or other educational concepts manifest differently across diverse populations. The realm of XAI in education is still in its nascent stages (Adadi & Berrada, 2018; Angelov et al., 2021; Barredo Arrieta et al., 2020). Future studies could focus on a more profound integration of XAI with student agency analytics, which could offer deeper insights into how different elements influence student agency and how it can be enhanced. A potential method to utilize could be explainable clustering (Bandyapadhyay et al., 2023).

The concept of teachers' professional noticing, especially in the context of adaptive teaching (Corno, 2008; Gallagher et al., 2022; Gibson & Ross, 2016; Rooney & Boud, 2019) could be a topic for future research. Can training in professional noticing enhance the outcomes of adaptive teaching? Can analytics tools like student agency analytics be developed to enhance teachers' noticing skills, offering them real-time insights into student behaviors and needs? Additionally, the potential of combining LLMs with prompt engineering in educational research is beginning to gain traction. Future research could examine how LLMs, guided by well-crafted prompts, could simulate complex educational scenarios, thereby providing educators and researchers with a dynamic tool for understanding and enhancing student learning experiences. Specifically, the interplay between LLM-generated content and real-world educational interventions, informed by computational psychometrics like student agency analytics, could be a fertile ground for research, potentially informing personalized learning pathways and pedagogical strategies.

Lastly, considering a wider perspective by drawing from the ANT and the postdigital stance (Matthews, 2019), it would be interesting to examine how human and non-human actors, such as learning analytics tools, collaboratively shape educational trajectories, outcomes, and experiences. These tools, like student agency analytics, are not passive entities but aim to actively influence learning and teaching processes, potentially giving rise to data agency and augmented agency. As novel applications of adaptive AI and learning analytics emerge, ANT and the postdigital lens can enlighten how these technologies and human actors intertwine, mutually shaping and being shaped. In conclusion, combining AI, computational psychometrics, adaptive learning, and adaptive teaching offers many research opportunities.

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