



# WP3: Participatory Action Research on Needs and Prioritisation Map



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## Chapter 2 Successful implementation of ITS in higher education. How can AI be used in higher education today?

### 2.1 Introduction

The rapid expansion of research in digital education is evident across various fields, including teaching and learning practices, career guidance, tutoring, skills and knowledge assessment, and academic management. This growth is driven by the increasing adoption and innovation of digital technologies within educational settings (Car et al., 2019). In fact, digital technology has become central to higher education, significantly influencing student engagement and the overall student experience (Bond et al., 2020). The COVID-19 pandemic has further accelerated digital transformation, prompting leaders to adapt to this new reality and explore its implications (Laufer et al., 2021).

With this growth, there is a heightened demand for education and training in areas such as gamification, artificial intelligence, and big data analytics (Soma & Nuckchady, 2021). Integrating digital skills development has also become a challenge in vocational schools and cooperative higher education institutions due to the increased use of internet and communication technologies among students and teachers (Wild & Heuling, 2020). Studies highlight the multidimensional nature of digital education, emphasizing aspects such as openness, quality, and the development of alternative credentials (Veletsianos et al., 2021). Therefore, the impact of digitalization on learning outcomes and various sectors beyond education is a key area of interest (Qureshi et al., 2021).

The transformation of the educational environment due to digitalization leads to a shift in cultural values and an emphasis on developing cognitive, interpersonal, and intrapersonal skills among learners. Research shows that the readiness and accessibility of technology positively influence student learning outcomes. Today, many higher education institutions face the challenge of addressing diverse technological readiness levels among students, with deficiencies in information and digital literacy posing obstacles to success (Buzzetto-Hollywood et al., 2018).

The integration of technology into teaching practices is essential for successful teaching and impacts student outcomes (Mollaei & Riasati, 2013). Consequently, technology in education has evolved from being a cost to be a critical factor in student success.

Moreover, faculty members' technical proficiency is crucial, especially in institutions offering technology-driven programs, as it significantly impacts student success. In fact, educators' acceptance and utilization of technology, including assistive technologies, play a vital role in enhancing student success. Technology-driven assessment strategies and activities are critical for improving student success rates (Khumalo, 2018).





In terms of student retention, technology enhances engagement. Tinto (Tinto, 2023) found that student engagement is critical for retention, and technology can facilitate this through online forums, interactive materials, and personalized feedback systems. Providing various tools and resources helps create a supportive learning environment that encourages persistence and success. A meta-analysis by Tamim (Tamim et al, 2011) demonstrated that technology-enhanced learning environments positively affect student achievement. Incorporating multimedia resources, adaptive learning platforms, and data analytics allows educators to tailor instruction to individual needs, improving learning outcomes.

Technology is essential for student enrolment, retention, and educational outcomes in higher education. Introducing new technologies can attract and retain students, enhance engagement, and improve overall outcomes. Thus, universities must explore innovative ways to integrate technology into their practices to ensure student success in the digital age.

The future of programming education is of great interest in the fields of education and technology. As information technology evolves, its role in education becomes increasingly significant. Integrating technology in educational settings enhances learning experiences, improves student engagement, and provides new opportunities for collaboration and peer learning. Collaboration and peer learning are key components of effective programming education, as working together allows students to learn from each other, share ideas, and solve complex problems. Peer learning also fosters teamwork and communication skills, essential in technology fields. Digital education offers advantages such as scalability, flexibility, and adaptability, making it a promising approach for new peer learning practices. In this new perspective, Artificial Intelligence (AI) has the potential to revolutionize higher education by enhancing teaching and learning processes.

## **2.2 Artificial Intelligence in HEIs: potentialities and threats for improving academic processes and practices**

tutoring methods supported by Artificial Intelligence (AI) are an exciting development in programming education. AI technologies have been increasingly applied in higher education, with a focus on automating teaching and learning tasks to enhance the student learning experience, provide student support, and improve enrolment management (Hannan & Liu, 2021). Moreover, AI-powered tutoring systems can provide personalized learning experiences, adapt to individual student needs, and offer real-time feedback and support. The aim is to provide a service tailored to the specific needs and learning style of individual students. By analyzing student performance data, AI tutors can identify areas where students are struggling and provide targeted interventions to help them improve their programming skills. Several studies have highlighted the various applications of AI in higher education, such as profiling, prediction, assessment, evaluation, adaptive systems, personalization, and intelligent tutoring systems (Zawacki-Richter et al., 2019; Bozkurt et al., 2021). By leveraging





AI technologies, higher education institutions can analyze vast amounts of data to gain insights into student performance and tailor instruction to individual needs. This can lead to improved learning outcomes and increased student satisfaction. AI-powered adaptive learning platforms can analyze student data in real-time to provide personalized recommendations and feedback, helping students improve their understanding and retention of course material. Additionally, AI can assist in the grading process by automating the evaluation of assignments and exams, allowing educators to focus more on providing valuable feedback and support to students. AI assistance in data analysis can identify trends and patterns in student performance, helping educators in making informed decisions about instructional strategies and interventions. Promoting self-directed learning is a frontier that AI can face developing virtual tutors and intelligent learning systems. The potential lies in the improvement of instructional delivery, personalizing learning experiences, automating administrative tasks, and providing valuable insights into student performance and outcomes. Gamified learning platforms, virtual reality simulations, and chatbots can motivate students' engagement in learning, making it more enjoyable and leading to higher levels of commitment. Automating administrative tasks, such as grading assignments and managing schedules, frees up educators' time to focus on more meaningful interactions with students. From personalizing learning experiences and adapting curricula to analyzing data for informed decisions, AI tools are reshaping education's landscape in unprecedented ways. By harnessing the power of AI, educators can create dynamic and engaging learning environments that equip students with the skills and knowledge they need to excel in the modern world.

Based on the above considerations, it is clear that Artificial Intelligence promises to transform higher education by enhancing learning, research, and leadership in schools and universities. However, the integration of AI in higher education comes with significant challenges, requiring a deeper engagement with its societal implications to ensure successful implementation (Bearman & Ajjawi, 2023). Despite over 30 years of AI use in education, there remains a limited understanding of its effects on teaching and learning in higher education (Durso & Arruda, 2022). The potential of AI to enhance teaching and learning in higher education is acknowledged (Slimi, Z., 2022), but there is a need for more investigation on the adoption of AI in this context (Crompton & Song, 2021). Researchers agree that there is a lack of critical reflection on the pedagogical and ethical implications of AI in higher education (Bozkurt et al., 2021). The integration of AI is a significant development that requires careful consideration of ethical and educational approaches (Zawacki-Richter et al., 2019). It is crucial to balance AI-driven enhancements with the essential human touch that educators provide, ensuring technology augments rather than replaces the human connection at the heart of education. Addressing potential obstacles to AI-supported teaching and learning is essential for successful implementation (Watanabe, 2023). To fully realize the benefits of Artificial Intelligence in higher education, social, cultural, and ethical issues related to bias, fairness, privacy, transparency, fairness, and security must be considered. Without careful consideration of these issues and proactive oversight, AI could exacerbate inequality,





undermine trust in institutions, and perpetuate bias against marginalized groups. Additionally, the resource requirements for responsible AI implementation—such as technical staff, data infrastructure, management systems, and ongoing funding—pose challenges for some institutions. Faculty, staff, and students may resist AI due to concerns about job threats, dehumanization of education, and a lack of transparency in algorithm-based recommendations. These challenges suggest that AI initiatives should be implemented after careful research and testing, and in a way that is consistent with educational priorities, ethical principles, and societal values. Addressing these challenges and finding solutions highlights the need to strengthen university management to promote AI integration in higher education. University strategic leadership plays a critical role in guiding appropriate AI adoption and innovation to balance benefits and risks. Examples of strategic actions that educators can pursue include articulating an AI vision within the context of broader institutional goals, fostering a campus climate that embraces experimentation and thoughtful adoption of AI tools, ensuring transparency and oversight of AI initiatives, and allocating resources to support ethics. Educators need a deep understanding of AI opportunities, trends, challenges, and applications specific to higher education to distinguish hype from reality, critically evaluate vendor offerings, and formulate AI investment strategies that maximize benefits while minimizing potential harm.

In conclusion, with the rise of Artificial Intelligence, education faces two challenges: reaping the benefits of AI to improve education processes, both in the classroom and at the system level, and tooling up students with new skills for increasingly automated economies and societies. While AI applications are still in their infancy, numerous promising examples suggest how AI could revolutionize education. As mentioned before, with reference to the classroom, AI can accelerate personalized learning (Panigrahi & Joshi, 2020) and support for students, while at the system level, it delivers predictive analysis to reduce dropout, and assess new skill sets. A new demand for complex skills that are less easy to automate (e.g. higher cognitive skills like creativity and critical thinking) is also the consequence of AI and digitalisation. Reaching the full potential of AI requires that stakeholders trust not only the technology, but also its use by humans. This raises new policy challenges on “trustworthy AI”, encompassing the privacy and security of data, but also possible wrongful uses of data leading to biases against individuals or groups (Vincent-Lancrin & van der Vlies, 2020). The successful implementation of ITS based on AI tools in higher education has the potential to transform learning, research, and leadership in colleges and universities (Tarisayi, 2023). AI can be used to personalize teaching, provide formative feedback, identify at-risk students, accelerate research discovery, and streamline administrative processes (Tarisayi, 2023). It must be clear that AI based ITS are not a competitor to human teaching, but rather an auxiliary tool that can enhance various operations and improve the educational process. The adoption of AI in higher education can be facilitated by understanding the implications for teachers and students, and by using adoption theories and models (Chatterjee & Bhattacharjee, 2020).





## 2.3 Limitations and Challenges in implementing Intelligent Tutoring System in Higher Education

Implementing Intelligent Tutoring Systems in higher education presents a range of limitations and challenges that must be carefully considered. These include technological barriers, integration issues, and the need for substantial investment in both time and resources to ensure effective deployment and utilization.

### 2.3.1 Dataset availability and explainability of AI techniques

Intelligent Tutoring Systems aim to provide individualized instruction by modeling learners' psychological states (Ma et al., 2014). They have been developed and evaluated over the last few decades, with a focus on applying Artificial Intelligence and cognitive science in education. Intelligent learning diagnosis is crucial for ITS, as it estimates learners' current knowledge mastery status and predicts their future learning performance (Wang et al., 2022). However, integrating ITS into education has proven difficult (Modén et al., 2021). Transitioning to more accessible and flexible education models, ITS can help move away from traditional teaching methods. The development of ITS has been a focus of applying Artificial Intelligence and cognitive science in education. Despite the challenges, ITS have shown statistically significant improvements in student learning outcomes compared to traditional teaching methods.

A significant challenge is the availability and quality of datasets for training and testing ITS. Without sufficient and relevant data, the performance and effectiveness of the system may be compromised. Researchers need to ensure that the datasets are comprehensive, diverse, and representative of the target student population to enhance the accuracy and reliability of the ITS. Another challenge lies in explaining the AI techniques employed in ITS to educators, students, and other stakeholders. Understanding how AI algorithms work and how they contribute to the learning process is crucial for gaining acceptance and trust in the system. Communicating complex AI concepts in a clear and accessible manner will facilitate the adoption of ITS. Advancements in AI, such as machine learning, natural language processing, and deep learning, can significantly improve the adaptability and personalization of ITS. However, further research and development are needed to leverage these techniques effectively in educational contexts and address specific challenges such as individualized learning paths, real-time feedback, and adaptive assessments. Additionally, more research is needed on software engineering practices specifically tailored to the design, development, and maintenance of ITS. Creating ITS requires interdisciplinary expertise in AI, education, psychology, and computer science, making it crucial to establish best practices and guidelines for ITS development. Research in software engineering for ITS can streamline the design process, enhance system scalability and reliability, and support the integration of new technologies and pedagogical methods. Addressing the limitations and challenges in



implementing ITS in higher education requires a concerted effort from researchers, educators, and developers.

### 2.3.2 Data Privacy and Ethics

According to the concerns of faculties to use ITS (Wang et al., 2020), data privacy and ethics still represent another relevant challenge for implementing ITS in higher education. The elaboration of extensive student data raises issues regarding privacy and ethical use. The effectiveness of ITS has been evaluated, indicating that the results are influenced by the nature of control treatments and the adequacy of program implementations (Kulik & Fletcher, 2015). Despite offering strong learning gains, ITS are traditionally designed for most-developed countries, posing a challenge when scaling them up to mainstream educational contexts (Nye, 2014).

The topic will be discussed in detail in Chapter 4, but here it seems useful to anticipate and underline some points of discussions. The literature comparison highlights the urgent need to address student data privacy protection in AI-driven education, with increasing attention to ethical risks from various stakeholders. It underscores the necessity of establishing a robust data protection framework encompassing information privacy, anonymity, surveillance, autonomy, non-discrimination, and information ownership (Huang, 2023).

Willis (Willis III, et al., 2016) discusses the growth of learning analytics techniques, the need for ethical reflection on student data collection, and presents an analysis of ethical review processes at three research institutions. However, the study shows some limitations, suggesting the need for further research, deeper development of more extensive approval guidelines, and presents the awareness of ethical issues related to learning analytics. It acknowledges limitations in providing a comprehensive understanding of the phenomenon and points out that the main actor in the process is the lecturer, excluding other stakeholders.

### 2.3.3 Bias

Researchers in education have recently begun drawing attention to existing cases of algorithmic bias in educational technologies. In fact, the possible increase, due to the adoption of AI and machine learning tools, may result in harmful impacts. AI algorithms may perpetuate existing biases in education, leading to inequitable outcomes. As a starting place in understanding the origins of algorithmic bias, Mitchell (Mitchell, S. et al. 2021) makes a helpful distinction between statistical and societal forms of bias, where the first ones encompass sampling bias and measurement error, while societal bias refers to “concerns about objectionable social structures that are represented in the data”. AI algorithms used in ITS have the capability to perpetuate existing biases in education, which can ultimately result in inequitable outcomes for students.





Addressing bias in algorithms within ITS means dealing with bias present in the data used to train these systems. If historical data used to train the AI algorithms contain biases, such as gender or racial biases in grading or student performance, the ITS may inadvertently learn and perpetuate these biases. This can lead to discriminatory outcomes for students from marginalized groups, further exacerbating existing inequalities in education. Algorithmic bias has been documented in situations ranging from at-risk prediction for high school or college dropout, at-risk prediction for failing a course (Hu & Rangwala, 2020; Kizilcec & Lee, 2020), automated essay scoring (Bridgeman et al., 2012), assessment of spoken language proficiency (Wang et al., 2018), and even the detection of student emotion (Ocumpaugh et al., 2015).

Moreover, the complexity of AI algorithms used in ITS can make it challenging to identify and effectively mitigate biases. These algorithms often operate as “black boxes”, meaning that the decision-making process is not transparent or easily interpretable. As a result, it can be difficult for educators and administrators to understand how biases are being perpetuated within the system and to intervene to address them.

Another limitation in implementing ITS in higher education is the lack of diversity and inclusivity in the development teams creating these systems. This limitation is further compounded by interoperability issues, which make it difficult to deploy these systems in educational platforms. To address these challenges, Santos (Santos et al., 2013) proposes a new approach to implement open-source and interoperable ITS. Woolf (Woolf, 1988) suggests incorporating community expertise to enhance the competence of current tutors, while Bonner (Bonner et al., 2016) highlights the complexities of building ITS for teams and provides a recommended process for authoring team based ITS. If the teams responsible for designing and developing ITS lack diversity, they may inadvertently embed their own biases into the algorithms, further perpetuating inequities in education. Then, it is essential for higher education institutions to prioritize diversity and inclusivity in the development and implementation of ITS. This includes ensuring that data used to train AI algorithms are regularly audited for biases and that mechanisms are in place to address and mitigate any identified biases. Additionally, transparency in the decision-making process of AI algorithms is crucial to enable educators to understand how these systems operate and to intervene when biases are detected.

### 2.3.4 Implementation Costs

Implementing ITS in higher education faces significant challenges also in terms of implementation costs and the technical expertise required (Kulik & Fletcher, 2015). In fact, deploying AI technologies in higher education requires significant financial investment and technical expertise. The financial investment needed to deploy AI technologies in higher education is substantial, and the expertise necessary to effectively integrate these systems is crucial (Kulik & Fletcher, 2015). Despite the potential learning gains offered by ITS, the costs





and technical demands associated with these systems pose barriers to widespread adoption, especially in developing countries (Nye, 2014).

The scalability of ITS to mainstream educational settings has been a notable challenge for the research community (Nye, et al., 2018). While developers aim to enhance the use of Information and Communication Technology (ICT) in ITS, limitations in data provision and ICT infrastructure in developing countries hinder implementation efforts. Additionally, the willingness of faculty to embrace ITS in the era of AI is a critical factor in the successful integration of these systems (Wang et al., 2020).

The sophistication of software capable of replicating the social-emotional and cognitive roles of educators is essential for the widespread use of ITS (Hughes, 2022). Furthermore, challenges such as technical infrastructure requirements, teacher training, data privacy, security, and ethical considerations need to be addressed when implementing AI in education, including physics education (Mahligawati, 2023).

### 2.3.5 User Acceptance

Resistance from some students and educators towards AI-driven tools can hinder the successful integration of ITS in educational settings, since they may be resistant to adopting AI-driven tools, preferring traditional teaching methods. Individuals may be hesitant to embrace AI technologies due to concerns about job displacement, lack of trust in machine-based systems, or simply a preference for traditional teaching methods. One of the key reasons for user resistance is the fear of job displacement among educators. Some teachers may perceive ITS as a threat to their roles, fearing that AI technologies could replace them in the classroom. This apprehension can lead to reluctance in adopting ITS and may result in a lack of support for its implementation.

Moreover, the lack of trust in machine-based systems is another significant factor contributing to user resistance. Students and educators may question the accuracy and reliability of AI-driven tools, especially in complex educational tasks that require human intervention and understanding. This skepticism towards ITS may slow its acceptance. Some educators may have strong beliefs in the effectiveness of conventional teaching approaches and may be reluctant to incorporate technology-based solutions into their teaching practices. The preference for traditional teaching methods over AI-driven tools limits the potential benefits in enhancing ITS learning outcomes (Chocarro et al., 2021). Addressing the concerns related to job displacement, building trust in machine-based systems, and promoting the benefits of AI-driven tools are essential steps to overcome resistance and facilitate the successful integration of ITS in educational settings.



## 2.4 Implementing Intelligent Tutoring System in Higher Education

Implementing an ITS in higher education necessitates a comprehensive understanding of research directions to effectively guide its development and deployment. Research directions denote the paths and patterns of research endeavors, offering insights into the evolution and outcomes of various studies. By outlining these trajectories, it becomes possible to track the progression of research topics over time, aiding in the identification of emerging trends and areas of focus within a particular field. Analyzing trajectories in educational research enables educators to tailor ITS content and delivery to cater to diverse learner needs. They inform the development of algorithms predicting student learning paths, enabling timely and targeted interventions to support student progress. Furthermore, research trajectories in the field of computer science can offer valuable insights into trajectory planning for intelligent systems, such as robots used in educational settings. Trajectory planning algorithms can, also, enhance the effectiveness of ITS by optimizing the delivery of educational content based on individual student trajectories and learning preferences (Li et al., 2023). Leveraging research directions from diverse fields like education, computer science, and psychology significantly enhances ITS design and implementation.

This section is devoted to the exploration of four crucial domains: Personalized Learning Experiences, Student Dropout Prevention, Tutoring and Academic Career Guidance, Students Performance Analysis. After presenting the main aspects of the topic, a few case studies are presented.

### 2.4.1 Personalized Learning Experiences

AI-assisted systems have been developed for personalized learning, adaptive testing, intelligent tutoring systems, learning analytics, and content creation. A number of studies have explored the potential of AI-powered systems to provide personalized learning experiences tailored to individual student needs. Rizvi (Rizivi, 2023) emphasizes the ability of these systems to adapt to students' strengths, weaknesses, and learning styles, specifically highlighting the use of machine learning, natural language processing, and data mining. Chaplot (Chaplot et al., 2016) and Fernandes (Fernandez et al., 2023) further delve into the technical aspects, with Chaplot proposing a new adaptive learning system architecture using neural networks, and Fernandes leveraging supervised machine learning techniques to schedule assignments and educational activities based on students' needs and preferences. However, ethical, and societal implications, as well as the need for further research, are also highlighted by Tiwari. Recently, Fernandes (Fernandez et al., 2023) leveraged effective Supervised Machine Learning (ML) techniques to adaptively schedule assignments and educational activities based on the students' needs, preferences, and background. The proposed intelligent system is trained based upon different academic factors from student learners' characteristics such as proficiency level, interest level, remote/in-person preference,



and assignment type preference and prescribes a proper learning plan to maximize the students' overall grade and satisfaction rate at the end of course. In addition, they conduct analysis of demographic parameters such as gender and race and their effects on students' success and academic satisfaction. A comprehensive analysis of five different machine learning models for ITS including Logistic Regression (LR), K-Nearest Neighbours (KNN), Support Vector Machine (SVM), Decision Tree (DT), and Random Forest (RF) are examined in (Fernandez et al., 2023).

### Case study 1: Carnegie Learning's MATHia

The platform offers tailor-made activity courses for children aged 5 to 11, and it offers several key features: One-on-One Coaching, Student Reports, Educator Reports and LiveLab that is a sort of MATHia that mirrors a human math coach by delivering real-time feedback and support to students. Carnegie Learning's MATHia platform has been the subject of several studies. Fancsali (Fancsali et al., 2014) found that the platform's personalization, including the use of learner-specified interests and friends' names, was associated with better learning outcomes. Miranda (Miranda et al., 2015) highlighted the importance of personalized learning objectives in mathematics, a feature that MATHia provides. Ritter (Ritter et al., 2016) discussed the practical implementation of MATHia in real-world classrooms, while Kalloo (Kalloo et al., 2010) emphasized the role of personalization in a game-based mobile learning application for mathematics. These studies collectively underscore the effectiveness of MATHia's personalized approach in improving students' math skills. Other interesting studies based on MATHia are:

1. EMERALDS Study (2021) used anonymized student data from MATHia to evaluate predictors of success in Algebra I. Completion of more workspaces in MATHia led to better performance in Algebra I, especially for students who had low test scores in middle school. MATHia helps close the gap for students who need it most. (<https://www.businesswire.com/news/home/20210721005130/en/Carnegie-Learning-Announces-New-3rd-Party-Study-Indicating-That-MATHia-Leads-to-Better-Performance-in-Algebra>).
2. A randomized field trial within MATHia explored whether rewriting content in “word problems” improved student mathematics performance, particularly among emerging English language readers. The study demonstrated positive effects of the rewrite intervention ([https://link.springer.com/content/pdf/10.1007/978-3-031-36336-8\\_30](https://link.springer.com/content/pdf/10.1007/978-3-031-36336-8_30)).
3. Scalable and Equitable Math Problem Solving Strategy Prediction in Big Educational Data (<https://arxiv.org/pdf/2308.03892.pdf>). This study introduces an AI-driven method to identify students' problem-solving strategies in mathematics. By employing mastery-based embeddings (MVec) and non-parametric clustering, the approach ensures fair and accurate predictions across diverse skill levels. Utilizing real-world datasets from MATHia, the model demonstrates scalability and effectiveness in enhancing personalized learning.





4. Rewriting Math Word Problems to Improve Learning Outcomes for Emerging Readers: A Randomized Field Trial in Carnegie Learning's MATHia ([https://link.springer.com/chapter/10.1007/978-3-031-36336-8\\_30](https://link.springer.com/chapter/10.1007/978-3-031-36336-8_30)). The study investigates whether modifying the language of math word problems can enhance performance among emerging English readers. Conducted with over 12,000 students, the trial utilized AI-driven methods to identify learners likely to benefit from simplified problem statements.

### 2.4.2 Student Dropout Prevention

ITS have demonstrated effectiveness in various domains, including student dropout prevention. By harnessing AI capabilities, these systems can analyze data to identify students at risk of dropping out and provide timely interventions. For example, Georgia State University's Panther Retention Grant program uses predictive analytics to pinpoint such students and offer financial assistance to help them remain in school. Similarly, the University of Arizona has implemented an early alert system driven by AI to detect students in jeopardy of dropping out and offer targeted support services.

Nye (Nye, 2014) suggests that while ITS have historically been developed for more affluent nations, their potential to enhance learning outcomes is widely acknowledged. These systems, as described by Laaziri et al. (2019), replicate the behavior and guidance of human tutors to deliver personalized support and enhance the learning process. Additionally, Aleven (Aleven et al. 2016) showcases how ITSs can expand educational reach by customizing instruction based on students' knowledge, making them valuable tools in tackling issues like student dropout rates. By integrating AI and metacognitive feedback (as discussed by Roll et al., 2011), ITSs can improve students' help-seeking skills, thereby contributing to student success and retention. By tailoring instruction to individual needs, ITS provide adaptive training experiences that cater to specific learner requirements, potentially reducing dropout rates. The utilization of ITS in student dropout prevention represents a promising field that merges AI capabilities with personalized support to identify at-risk students and deliver interventions that can enhance retention rates.

#### Case study 2: Georgia State University's Panther Retention Grant program

Georgia State University's Panther Retention Grant program is a notable initiative aimed at preventing student dropouts through the utilization of predictive analytics. This program is designed to identify students who are at risk of dropping out and provide them with financial assistance to support their academic journey. By leveraging predictive analytics, the university can proactively identify students who may be facing challenges that could lead to dropping out and intervene to provide the necessary support. One key reference that provides insights into the Panther Retention Grant program at Georgia State University is a study by Goldrick-Rab (Goldrick-Rab et al., 2016). This study highlights the importance of financial assistance in





promoting college completion and underscores the significance of programs like the Panther Retention Grant in supporting at-risk students. Another relevant reference is a research article by Bettinger and Baker (Bettinger & Baker, 2011). This study examines the impact of student coaching and mentoring programs on student outcomes, including retention and graduation rates. Such mentoring programs, similar to the support provided through the Panther Retention Grant program, have been shown to positively influence student success and persistence in higher education. Furthermore, a report by the National Association for College Admission Counseling (NACAC) on "Predictive Analytics in Higher Education: Five Guiding Practices for Ethical Use" offers insights into the ethical considerations associated with the use of predictive analytics in higher education. This report emphasizes the importance of ensuring that predictive analytics are used responsibly and ethically to support student success and retention, as exemplified by the Panther Retention Grant program at Georgia State University. Panther Retention Grant program at Georgia State University represents a proactive approach to student dropout prevention through the strategic use of predictive analytics and financial assistance. By referencing studies such as those by Goldrick-Rab (Goldrick-Rab et al., 2016) and Bettinger and Baker (Bettinger & Baker, 2011), as well as reports like the one by NACAC, we can gain a comprehensive understanding of the significance and impact of such initiatives in promoting student success and retention in higher education.

### **Case study 3: AI powered early alert system powered at University of Arizona**

The University of Arizona's implementation of an early alert system powered by Artificial Intelligence (AI) to identify students at risk of dropping out and offer tailored support services is a significant advancement in the field of education. This innovative approach leverages AI technology to analyze various data points and patterns to predict student outcomes accurately. By utilizing this system, the university aims to intervene proactively and provide timely assistance to students who may be facing challenges that could lead to dropping out. One key reference that provides insights into the University of Arizona's early alert system is the research article by Arnold and Pistilli (Arnold & Pistilli, 2012). This study discusses the implementation of a similar early alert system at Purdue University, which utilized predictive analytics to identify students at risk of academic failure. The findings highlight the effectiveness of such systems in improving student retention rates and academic performance. Another relevant reference is the work by Dawson and McWilliam (Dawson & McWilliam, 2008) on "Investigating the application of IT-generated data as an indicator of student progress." This study explores the use of IT-generated data, including learning management system interactions and assessment results, to predict student success and retention. The research demonstrates the potential of leveraging technology to support student success initiatives and enhance educational outcomes.





### 2.4.3 Tutoring and Academic Career Guidance

AI-based systems can provide tuition for specific topics or subjects in very interactive and interesting ways, which also do not require humans to explain concepts and answer questions. Later, it can also be extended to automate school or college education, integrating difficult-to-maintain knowledge from a particular human teacher. ITS systems work on a knowledge base to provide personalized reactions to student input and intelligent behavior. They also aim to ease tutoring for teachers with multiple students or cumbersome students. Now, ITS can be used to mimic the behavior of a human teacher for a particular subject, and the aim is to integrate in-depth knowledge from various sources and expert-level decision-making to cover the AI-complete task. AI can also be used for guidance counselling and distance education in a favored manner.

#### Case study 4: IBM Watson's AI-powered virtual advisor

IBM Watson's AI-powered virtual advisor is made to understand and provide effective responses to inquiries asked in regular natural language for a conversational interface and can be taken to any implementation corresponding to a robot, a PC, or a mobile device. The system uses XML technology to input a predefined set of data on the knowledge base for a specific field so that the virtual advisor can effectively answer and provide information to the user. The conversation is analyzed and broken down, and with the use of a finite state transducer, the most appropriate response is matched by picking the most appropriate path with the most matched keywords to select the most appropriate response. A hit score is generated by comparing the input conversation to a database of indexed keywords and most frequent responses to closely match the input with the best response.

A range of studies has explored the potential of IBM Watson's AI-powered virtual advisor in the education sector. Asakiewicz (Asakiewicz et al. 2017) and Gaglio (Gaglio et al., 2019) both developed virtual advisors using Watson technology to support students and staff in a university setting. These advisors were designed to answer questions, provide information, and help in various areas, including course selection and career planning. Vijjapu (Vijjapu, 2019) further enhanced the capabilities of the virtual advisor by incorporating machine learning techniques to aid in educational planning and academic advising.

IBM Watson's AI-powered virtual advisor can potentially assist students in course selection, career planning, and accessing support services. By creating an academic information system that can be accessed by the student everywhere and every time, the students can find the information that they need without contacting the lecturers or the administrators. Nevertheless, providing these various types of student support requires huge efforts, especially in the case of academic monitoring and providing detailed information for all the students. For academic monitoring, it can be done by extracting the academic data and processing them. This method is very efficient instead of monitoring each student one by one. IBM Watson's AI-powered virtual advisor used to make academic monitoring even more efficient by creating a system that can be used to simulate the student's academic condition. This virtual system behaves





like the real student, and it can stop whenever there is a problem with the student. This system appears to be helpful to ease administrators in determining what should be done to provide support to the student.

#### 2.4.4 Student Performance Analysis

AI can analyze academic performance data to identify patterns and trends, enabling educators to provide targeted support.

Several educational databases have been proposed, which enabled the application of data mining to extract useful information on student's performance data that can be used to identify patterns and trends, enabling educators to provide targeted support. This led to the emergence of Education Data Mining (EDM) (Calvet Liñán & Juan Pérez, 2015; Dutt, et al., 2017) as an independent research field. Nowadays, EDM plays a significant role in discovering patterns of knowledge about educational phenomena and the learning process (Anoopkumar & Zubair Rahman, 2016), including understanding performance. Especially, data mining has been used for predicting various crucial educational outcomes, like performance, retention, success, satisfaction, achievement, and dropout rate.

AI has the potential to analyze academic performance data with the aim to identify patterns and trends, enabling targeted support for struggling students. This can be achieved using algorithms that predict student success and performance (Ricon-Flores, et al., 2020). However, the challenge lies in translating this data into actionable insights for educators (Pardo, et al., 2016a). Learning Analytics (LA) can provide a general picture of the group's performance, leading to overall improvement. Despite individual forecasts not being accurate, instructors can adapt teaching techniques for better results. Students believe that knowing predictive results at the start of the course can help them perform better. Nevertheless, providing learning analytics alone may not lead to changes in teaching practices. Pardo (Pardo, et al., 2016b) proposes a model to help instructors identify subpopulations of students for targeted support actions based on predicted exam scores derived from the learning design. The resulting model classifies students according to their predicted exam scores.

#### Case study 5: Brightspace Insights by D2L for student data analysis and recommendations

Brightspace Insights by D2L creates visual representations of a course data, allowing one to make informed decisions. Insights also supports the ability to "drill down" on widgets like the course access and student's last accessed activity to obtain details. Insight's dashboard is very customizable and allows you to rearrange the layout and add or remove the widgets displayed. Instructors can create their own dashboards for specific tasks. This can be done by creating the new dashboard on the right side of the screen and adding particular widgets to it, which can be chosen by clicking the dropdown on the widgets displayed on the screen. An effective and successful analyst is one who understands the technologies that he is working





with and intends to use so that the most can be drawn out of the data. This insight is an invaluable tool for those who are looking to enhance and improve their learning environment and the student experience. For example, student login and comment rates could be used to help design an intervention to identify at-risk students in a learning activity. Particularly powerful predictive models are used to determine what types of learning path intervention are needed to maximize student performance in a course or at a certain learning outcome. These models simulate various scenarios and provide the best help decisions to improve learner performance.

This aggregated data can be organized using multidimensional frameworks, such as defined rubrics, across all courses in the applied discipline from one or many institutions. Aggregate results against these frameworks are presented to provide insight into the teaching and learning process. For example, are the first-year students meeting the expected outcomes for a particular course? Subgroup analysis on performance against criteria or, in the case of learning paths, sequence of performance across criteria can provide a more profound understanding of the learning process. Available and accomplished course and student performance is made more transparent. Steering reports show aggregate student performance in a course. These reports compare to a previous state or specific outcome, indicating if the performance change was positive or negative.

At the time of writing, Brightspace Insights is available with the Learning Environment, Connect for Learning mixed model delivery, and predict. In both cases, data about the learning environment from the course activity, student interactions, and resulting performance can be automatically aggregated into a data mart.

### **Case study 6: Course Signals system at Purdue University**

Purdue University's Course Signals system, which uses predictive analytics to identify at-risk students, has been shown to be effective in improving student performance. Course Signals is a predictive analytic system built on Bayesian Theorem and predictive modelling designed to enhance course-level student success. At Purdue University, Course Signals was implemented in fall 2007 in courses with high D, F and Withdrawal (DFW) rates. The primary goals of Course Signals are to provide students with feedback on their performance in a course, to predict students' final course grade, and to provide advisors and faculty with information to help students succeed in their courses. The core educational issue addressed by Course Signals is student disengagement. Throughout the course of a semester, a large number of students fall behind in their coursework, and as a result, they become discouraged about their chances of success and reduce their effort in the course. If students can identify early and accurately when their chances of success in a course are in jeopardy, then with watching for undesirable states and a set of proposed intervention techniques, these students can be steered back onto the path of successful course completion. A more engaged student is a more successful student at Purdue. Further, an early feedback intervention system is an





effective and unobtrusive way to initiate dialogue with disheartened students about what led to their state and the best strategies for moving forward in their coursework.

Course Signals provides students with immediate feedback on their performance in undergraduate courses. The goal is to use this feedback on student behavior and performance data to create predictive models for student success and use these models to build an intervention system to improve retention and on-time degree completion. The original problem was to develop an intervention system for students, particularly freshmen, but the underlying goal is to improve undergraduate education at Purdue. It emerged from a project named Boilerfailure Early Intervention System, which was started in 2002. This program used data mining techniques to identify students at risk for poor performance in FYE courses and to notify their advisors. In 2007, Purdue University (West Lafayette campus) formed a task force to study the problems of high DFW rates and "student disengagement" in large enrollment courses. The task force recommended possible solutions, including developing an online system that students could use to check their performance in a given course. The Course Signals project was handed off to the Technical Assistance Program (TAP) and development began in fall 2007. The first pilot of the system was in Spring 2009 in 22 different courses across campus.

Corrigan (Corrigan et al., 2015) further demonstrated the potential of predictive analytics in improving test performance and providing early alerts to struggling students, respectively. These studies collectively highlight the value of using data-driven approaches to support student success.

## 2.5 Open Learner Model

Open Learner Modelling (OLM) is another crucial aspect of ITS research, focusing on the interpretability of AI representations (Conati et al., 2018). ITS contains intelligence and has four key components: the domain model, student model, teaching model, and learning environment (Freedman et al., 2000). The student model, which contains information about the student's background and learning preferences, is a fundamental component of an ITS (Panagiotopoulos, 2012).

Chang (2020) proposes an ontology-driven approach to represent pedagogical rules in an ITS, using data mining to automatically extract rules from tutoring sessions. These studies collectively highlight the importance of OLM in making AI representations interpretable and explainable in ITS research. In other words, OLM focuses on interpretability of AI representations in ITS research. OLMs aim to open up AI models of learners' cognition and emotions to support human learning and teaching. The research in ITS and OLM can serve as a foundation for an interpretable AI framework applicable beyond education contexts.

The main challenge here is to decide the most appropriate sequence of activities that can improve the average learning rate over all the skills. The methodology involves analysing various knowledge tracing methods and empirical methods for predicting a student's mastery





of a skill. The methodology involves Artificial Intelligence concepts, dynamic student modelling, human cognition, intelligent user interfaces, intelligent help systems, and the use of strategies. In this frame, domain independence is a key theme in ITS research, focusing on the reuse of knowledge across different domains. Nevertheless, task independence, which refers to the system's ability to support various student tasks, remains largely unaddressed in most systems. (Freedman et al., 2000).

Below, different techniques are reported for representing learners' background knowledge and preferences:

- **Cognitive Tutor** is the ITS platform developed by Carnegie Learning, whose functionality has been detailed above, that utilizes OLM to provide personalized instruction in mathematics. It adapts to individual student learning styles and preferences by continuously assessing their knowledge and skills, providing feedback, and offering tailored exercises and practice problems.
- **ALEKS (Assessment and Learning in Knowledge Spaces)** is an adaptive learning platform that incorporates OLM to assess students' knowledge gaps and deliver customized learning paths in subjects like mathematics, chemistry, accounting, and more. It uses sophisticated algorithms to dynamically adjust the difficulty of questions based on students' responses and learning progress.
- **SMART Learning Suite** is an integrated set of digital tools for interactive and collaborative learning. It includes SMART Notebook for lesson creation, SMART Response for formative assessment, and SMART amp for collaborative workspaces. While not strictly an ITS, SMART Learning Suite integrates OLM features to provide personalized learning experiences and track student progress over time.
- **DreamBox Learning** is an adaptive math program for students in kindergarten through eighth grade. It utilizes OLM techniques to tailor instruction to each student's level of understanding, learning pace, and preferences. DreamBox Learning also provides real-time feedback to both students and teachers, helping them monitor progress and identify areas for improvement.

## 2.6 Conclusion

Successful implementation of ITS in higher education involves leveraging AI techniques to provide personalized support, enhance collaborative learning, and strategically integrate digitization and virtual reality (VR) technologies into the learning environment. ITS can engage students in the learning process and provide personalized feedback, identify students' intentions, and support adaptive navigation. Additionally, AI can support collaborative learning by distinguishing learners working in collaboration and adapting the learning support system to individual and group needs. AI techniques can be used to diagnose errors in student solutions, recognize individual learners, and enable a conversation with students. They can be used to enhance the learning experience through virtual reality (VR) technologies. The





adoption of VR in education offers universities a wide range of options to improve the achievement of pedagogical goals. By strategically integrating digitization and AI into learning and teaching, universities can develop infrastructure and sustainability strategies that align with higher-level goals. AI can be successfully implemented in higher education using ITS. These systems leverage AI techniques to engage students in the learning process and provide personalized support. AI has the potential to transform higher education through personalized teaching, feedback provision, at-risk student identification, research acceleration, and administrative process streamlining. Empowering university leadership is crucial for successful AI adoption, and governance, strategic investment, and a human-centric approach are essential for maximizing the benefits in higher education. AI is considered an auxiliary, valuable tool in higher education, not a competitor to teaching staff. Its effective use can assist in selecting optimal learning strategies for students and meeting labor market needs. AI is an emerging technology with the potential to transform social interaction. As well, education can lead to personalized learning experiences and improved learning outcomes. Case studies of AI use in education are also provided. Integrating AI into higher education requires significant changes in both content and delivery, with a division of labour between AI and human educators being the optimal approach. Critical considerations for successful integration of AI tools in education include ensuring data privacy, addressing bias in algorithms, maintaining a balance between technology and human interaction, and preparing educators effectively.

In conclusion, main findings in this comparative review can be listed as follows:

- AI is effective in addressing students' needs and discovering their capabilities.
- Challenges in applying AI in higher education include high cost, lack of expert personnel, and weak soft skills.
- Machines are not ready to replace humans but can enhance human capabilities.
- Cognitive tutors improve learning outcomes in education.
- Balancing instructional assistance and self-directed learning is a challenge with AI-driven tools.
- AI tools in higher education provide numerous advantages at the institutional, social, and instructional levels.