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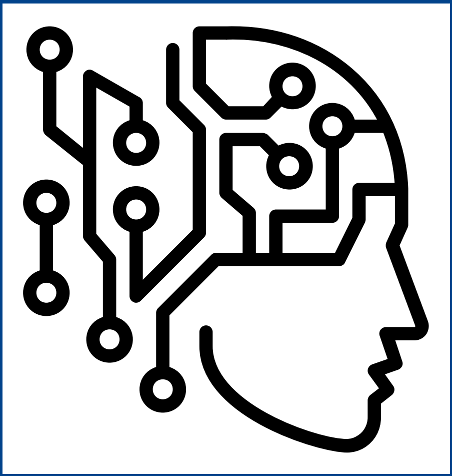
Artificial Intelligence Literacy and Social-Emotional Skills as Transversal Competencies in Education



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"Working together for a green, competitive and inclusive Europe"

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Summary

The SETCOM Monograph is a significant scholarly work that explores the intersection of Artificial Intelligence (AI) literacy and social-emotional (SE) skills within the educational context. This collection of scientific papers delves deeply into how AI and SE skills, as transversal competencies, can be developed and integrated into educational frameworks. The monograph is based on empirical studies conducted using the scientific method of pedagogical research, ensuring a rigorous and evidence-based approach to its findings. Central to the monograph is the exploration of AI's potential to transform educational experiences by providing personalised learning and the challenges associated with its integration. It discusses the technical and ethical considerations that must be navigated to effectively implement AI in teaching and learning. The monograph also emphasises the necessity for educators to develop competencies in AI alongside their social-emotional skills to address the dynamic demands of modern education. The various contributions within the monograph cover a broad spectrum, from technical aspects of AI and its ethical dimensions to in-depth insights into social-emotional learning. The authors present a comprehensive analysis of how AI can support and enhance educational methodologies and underscore the broader implications for education systems. Each paper within the monograph is rooted in empirical research, featuring data that has been meticulously collected and analysed. A key conclusion of the monograph is the significant potential for AI to benefit the educational environment when integrated with social-emotional learning. It suggests that a balanced, ethical approach to implementing AI in education can lead to equitable and transformative outcomes. The monograph serves as a valuable resource for educators, policymakers, and researchers, offering evidence-based insights into the integration of AI literacy and SE skills. It underscores the importance of these competencies as foundational elements for educators and learners in the evolving educational landscape.

Foreword

As we stand at the beginning of a new era in education, the SETCOM Monograph entitled Artificial Intelligence Literacy and Social-Emotional Skills as Transversal Competencies in Education presents a timely exploration of the intersection between Artificial Intelligence (AI) and social-emotional learning (SEL)—two pillars that are increasingly becoming vital in shaping the future of teaching and learning. The emergence of AI as a force in education offers an unprecedented opportunity to reimagine how learning experiences are crafted and delivered. The monograph rigorously examines the transformative potential of AI in the educational landscape, identifying it as a catalyst that propels personalized learning forward. However, it is not just the technological prowess of AI that this monograph brings into focus. It also shines a light on the human aspect—the development of social and emotional competencies that are essential in harnessing the full power of AI. The work presented here does not shy away from the complexities and the nuanced interplay of technology and human emotion. It delves into the essence of SEL and its critical role in forming the bedrock on which AI can be effectively integrated into the fabric of education.

This foreword serves as an invitation to engage with the content that follows, which is both a reflection of meticulous research and a forward-looking perspective on education. The discussions and findings within these pages are a call to educators, policymakers, and technologists to collaborate and navigate the challenges that accompany the adoption of AI in education. As AI continues to evolve and become more embedded in our educational systems, it is the balanced, human-centered approach advocated by SETCOM that will ensure technology enhances rather than undermines the educational experience.

The SETCOM Monograph begins with "The Technological Dimension of Artificial Intelligence in Education", which lays the foundation for understanding how AI can be integrated into educational practices and its implications for future learning environments. "Intersecting Evaluations: Digital Competence and AI Attitudes among Students" explores the perceptions of students, examining the relationship between their digital competencies and attitudes towards AI, a critical component for the effective use of technology in education. As the monograph progresses, "Educational Transformation: Exploring the Benefits of Generative AI Tools" discusses how generative AI tools can revolutionise educational methodologies, enhancing learning experiences and outcomes. Meanwhile, "The Oxymoron of AI in Education" takes a critical stance on the potential contradictions and challenges that AI presents within the educational sector. Further, "Responsible Decision Making in Use of Artificial Intelligence from Students' Perspective" emphasizes the importance of ethical considerations and informed decision-making when integrating AI into learning processes. The chapter "Synergy of Beliefs between Social-Emotional Learning and the Use of Artificial Intelligence Systems in Schools" presents a cluster typology analysis among students, highlighting how SEL and AI can complement each other to foster a more holistic educational approach. The monograph also examines "Differences in Perception of Social and Emotional Learning among Teachers Working at Different Educational Levels", providing insights into the varying perspectives on SEL across the teaching profession. Lastly, "Teachers' Attitudes about Social and Emotional Learning as Predictors of Their Relational Competence" identifies how educators' beliefs about SEL can be indicative of their ability to form and maintain relationships within the educational environment.

In its entirety, the SETCOM Monograph entitled underscores the complex but promising intersection of AI and SEL, advocating for a nuanced approach to incorporating these elements into the educational fabric. It suggests that when harmonized effectively, AI and SEL have the potential to not only enhance the learning experience but also to equip learners and educators with the necessary skills to navigate an increasingly digital future.

In essence, the SETCOM Monograph is a manifesto for a future where AI and SEL are not just parallel tracks but converging paths that lead to a holistic educational experience. It is a narrative of optimism, caution, and above all, a testament to the human spirit's ability to adapt and innovate. Let us embark on this journey with an open mind and a commitment to creating an educational environment that is as nurturing as it is enlightening.

Marta Licardo, Alenka Lipovec

The Technological Dimension of Artificial Intelligence in Education

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Abstract

This paper presents a thorough examination of the technological dimension of Artificial Intelligence (AI) in education, with a particular focus on Intelligent Tutoring Systems (ITS) and the impact on Socio-Emotional Learning (SEL). Initially, an overview of AI and its historical evolution sets the foundation for a deeper exploration into its educational applications. The paper extends to machine learning, reinforcement learning models, and the critical role they play in personalizing educational experiences. Through an investigation into individual student tutoring and immediate personalized feedback, the paper highlights the great potential of integrating AI in educational settings. Furthermore, the intersection of AI with SEL is explored, underlining the broader implications for the entire educational environment. The paper concludes with a synthesis of the findings, emphasizing the transformative potential of AI in education while acknowledging the need for a balanced and ethically informed implementation to ensure an equitable educational landscape.

Keywords: Artificial Intelligence in Education, Intelligent Tutoring Systems, Socio-Emotional Learning, Reinforcement Learning, Personalized Learning

Introduction

Artificial Intelligence (AI) is proof of human ingenuity and the relentless pursuit of creating intelligent machines. It has rapidly transitioned from science fiction to a driver of transformation across various sectors, including healthcare, finance, education, and beyond. In the educational field one of the important dimensions of AI is the technological dimension of AI, which covers a spectrum of elements, including advanced algorithms, adaptive learning platforms, data analytics, and evolving hardware configurations. These tech tools support the working of AI-powered educational systems and help shape the teaching methods used in modern education. Integrating AI in education goes beyond conventional teaching methods, offering personalized learning pathways, real-time performance analytics, and interactive learning environments. This paper aims to study the technological dimensions of AI within the educational sphere, considering the fundamental technical components, their synergistic interactions, and the subsequent implications for learning outcomes, accessibility, and ethical considerations. Our analysis aspires to contribute a well-rounded discourse on how the technological aspect of AI can be harnessed to improve teaching and learning.

Artificial Intelligence

In recent years, the term *artificial intelligence* has expanded significantly across various domains of discussion, evident in news outlets, social platforms, educational sectors, and casual conversations. Although the inception of AI can be traced back to the 1950s, its prominence in modern discourse has increased significantly in recent times. This surge can be attributed to significant advancements in computational capabilities over the past decade, facilitating the management of extensive data sets and subsequently broadening the horizon of possibilities within this domain. One notable manifestation of these advancements is the integration of AI systems into routine daily activities, enhancing efficiency and user engagement in various spheres of life.

The pervasive deployment of AI often takes place invisibly and blends seamlessly into normal interactions. A paradigmatic instance of this integration is observed in the deployment of AI-powered chatbots within online retail environments. As consumers traverse these digital platforms, they may encounter virtual assistants, ostensibly positioned as customer service representatives, who enhance the shopping experience by explaining return policies or assisting in product selection. Contrary to the perception of interacting with human operators, these virtual entities are in reality AI-driven chatbots adept at mimicking human interactions.

Another example of using AI in our everyday lives is browsing on the Web. Most browsers have implemented AI systems in their search engines to find the most relevant search results for users (Escandell-Poveda et al., 2022).

Other examples of using AI in our everyday lives are intelligent personal assistants like Siri from Apple, Google Assistant from Google, or Alexa from Amazon (Shum et al., 2018). They can play music, read a weather report, remind the user about upcoming events, recommend a restaurant based on the user's previous choices, etc.

The integration of Machine Learning (ML) based systems in critical domains with direct impacts on human well-being, life, and liberty, underscores the need to ensure the appropriateness, responsibility, and safety of such technological transference. The shift of decision-making authority from humans to ML models requires a robust assurance framework. Providing explanations of ML models and their generated predictions emerges as a crucial aspect of this assurance framework, furnishing evidence of the rationale behind automated decisions (McDermid et al., 2021).

The transference of decision-making from human educators to automated systems, within the educational environment, raises the need for critical assurance. This imperative seeks to verify the appropriateness, responsibility, and safety of such transference, ensuring that the educational integrity and the welfare of learners are upheld.

Artificial Intelligence in Education

AI is widely applied in different industries, and its implementation into education seems natural. However, while many believe AI can solve many core problems in education, such as the lack of qualified teachers and the growing achievement gap between rich and poor learners, these claims are often not backed by evidence (Holmes et al., 2022). When implementing AI in education, questions arise such as who will use AI tools (students, teachers, non-academic specialist support services, etc.), at which level of education, how does AI work, where and how the data is stored, etc.

The domain of Artificial Intelligence in Education (AIED) can be segmented into four central components (Holmes et al., 2022): Learning with AI, Utilizing AI to understand learning, Learning about AI, and Preparing for AI. The latter two are frequently conducted in tandem, encapsulated under the term AI literacy. This division is done to underline the significance of preparation for the integration and implications of AI.

Learning with AI covers the use of AI tools in learning and teaching. We categorize this component into learner-supporting AI, teacher-supporting AI and institution-supporting AI, based on the intended users of the tools.

Using AI to learn about learning involves utilizing AI tools to analyse data collected during learning with AI. This data, referred to as the learner's digital traces, includes information about what the learner clicks, their mouse movements, their reactions to questions, etc.

Learning about AI encompasses the assimilation of knowledge concerning the technical dimension of AI, termed as AI literacy: the technological dimension. This is aimed at ensuring a foundational understanding of AI techniques and technologies, like ML and natural language processing, amongst individuals. Acquiring this knowledge is very important in the modern technological world, as it empowers individuals to make informed and responsible decisions.

Preparing for AI entails the acquisition of knowledge concerning AI within the framework of ethical considerations, data bias, surveillance, and potential ramifications on employment. This is also referred to as AI literacy: the human dimension.

Holmes and Tuomi (2022) in their work summarize the taxonomy from Holmes et al. (2019), where AIED can be classified into three distinct yet overlapping categories: student-focused, teacher-focused, and institution-focused AIED. It should be noted that all the below-listed tools were not necessarily originally developed for educational use, but they were adapted for education when their utility was recognized.

Within the student-focused AIED category, Intelligent Tutoring Systems, AI-assisted Apps and Simulations, AI to support Learners with Disabilities, Automatic Essay Writing, Chatbots, and Automatic Formative Assessment, among others, were identified. Essentially, these AI tools play a vital role in aiding students in their learning processes, leading to improved academic outcomes.

Teacher-focused AIED encompasses tools such as Plagiarism Detection, Smart Curation of Learning Materials, Classroom Monitoring, and AI Teaching and Assessment Assistants. These tools are tailored to assist educators in various aspects of teaching and assessment.

Institution-focused AIED includes tools related to Admissions, Course Planning, Scheduling, and Timetabling, as well as identifying dropouts and students at risk. These applications cater to the institutional aspects of education, enhancing efficiency and decision-making within educational organizations.

Intelligent Tutors in Education

According to Holmes et al. (2019), the inception of student-focused educational technology can be traced back to the 1920s with the development of a multi-choice machine by psychologist Sidney Pressey. The device was originally developed as a test correction system, but Pressey observed that devices "… *clearly do more than test him; they also teach him."* (Pressey, 1950) He concluded that students were positively influenced by an immediate and automated response as to whether their answer was correct or incorrect, and therefore the machine represented the first mechanical device to assist learning.

Pressey's machine was followed in 1958 by psychologist B.F. Skinner, who developed a device for testing students' knowledge (Skinner, 1958). At the same time, it displayed the correct answer after each question was answered. This way of testing allowed an automated and immediate response, reminiscent of reinforcement learning. Skinner compared the usefulness of the device to learning with a private tutor.

Later, the development of intelligent tutors continued, and experts began to explore their contribution to education. In the 1990s, several studies on this topic emerged, which were later presented in Woolf's work (Woolf, 2009). To summarise, they all mostly conclude that intelligent tutors are competitive with individual human tutors, that they reduce the time taken to learn the material, and that they are more successful than traditional schooling. The authors of the studies have pointed to the advantages of intelligent tutors as being mainly the tailored, individualized treatment of each student according to his or her needs, which has also been the foundation for the development of the concept of AIED and intelligent tutors as we know them today, as AIED aims at a personalized, flexible, inclusive and engaging education (Luckin et al., 2016).

The History of Artificial Intelligence

The conceptualization of AI can be traced back to human artistic endeavours, as exemplified by the anthropomorphism of animals and inanimate objects in various forms of media, notably the portrayal of the 'Tin Man' in the 1939 musical, *The Wizard of Oz,* which subtly broached the idea of mechanized cognition. This artistic depiction catalysed speculative research into the cognitive capacities of machines, a query formally initiated by Alan Turing in 1950, resulting in the proposition of the Turing Test as a preliminary measure of machine intelligence (Turing, 1950). Despite the growing interest, the progression of AI encountered significant obstacles due to the inherent limitations of early computing devices, which were restricted to executing commands without retention capabilities, coupled with the prohibitive costs associated with computing resources, which limited AI research to wealthy academic and industrial entities. A seminal event in the AI chronicle was the Dartmouth Summer Research Project on Artificial Intelligence (DSRPAI) convened by John McCarthy and Marvin Minsky in 1956, wherein the term 'Artificial Intelligence' was officially coined, and the feasibility of AI was discussed by a group of researchers from the field. Although consensus on the scope and trajectory of AI remained elusive, the group acknowledged the potential reach of AI, thereby initiating an era of intensified research and exploration in AI that continued over the next two decades.

In the next years, the evolution of computers caused improvements in machine learning algorithms. The first chatbot known to the public was ELIZA, developed in 1966, (Shum et al., 2018; Weizenbaum, 1966), a natural language processing computer program that made some kinds of natural language conversation between humans and machines possible. Eliza simulated a conversation with a psychotherapist. Even though Eliza couldn't form complex and meaningful sentences, a lot of people believed that they were talking to a real person.

The big moment for the popularization of AI was in 1997, when the reigning world chess champion Gary Kasparov was defeated by a chess-playing expert system, Deep Blue (Hsu, 1999). In 2011, the intelligent speech assistant Siri was implemented in a mobile phone for the first time (Shum et al., 2018). The game of Go has long been considered one of the most challenging, because of the number of possible moves. In 2016, the computer program named AlphaGo (Silver et al., 2016) beat the winner of 18 world titles, considered the greatest player of the decade, Lee Sedol. The interesting part is that during the game, AlphaGo made a move which was at first marked by humans as an embarrassing mistake, but it turned out to be the winning move. The application of AI boomed after that.

Artificial Intelligence in Theory

Even though the research field of AI began developing in the 1950s and is currently gaining popularity, researchers still haven't agreed on its definition to this day. Of course, during years of research, there have been many definition proposals, but none of them was agreed to be the right one. It is natural to ask why. Well, the field of AI is very broad and covers different sciences, such as medicine, engineering, logistics, education, etc. As a result, each field has its own way of researching and applying AI, and a proposed definition from one field does not necessarily fit the others.

The lack of consistency in the definition of AI was also highlighted in a report by the Council of Europe (Holmes et al., 2022), which offered many definitions, one of them was proposed by UNICEF (Dignum et al., 2021): Machine-based systems that can, given a set of human-defined objectives, make predictions, recommendations, or decisions that influence real or virtual environments. AI systems interact with us and act on our environment, either directly or indirectly. Often, they appear to operate autonomously, and can adapt their behaviour by learning about the context.

AI is often equated with ML, which is wrong since ML is only a subcategory of AI. AI is usually presented as a combination of six disciplines, which are (represented in Figure 1):

- Machine learning (ML), the ability to automatically improve performance over time based on data and experience without being explicitly programmed for each task,
- Natural language processing (NLP), the ability to understand and process human language,
- Expert systems, the ability to simulate the decision-making abilities of a human expert,
- Speech recognition, the ability to convert speech to text and text to speech,
- Computer vision, the ability to perceive the world through images,
- Robotics, the ability to interact socially and manipulate the surroundings.

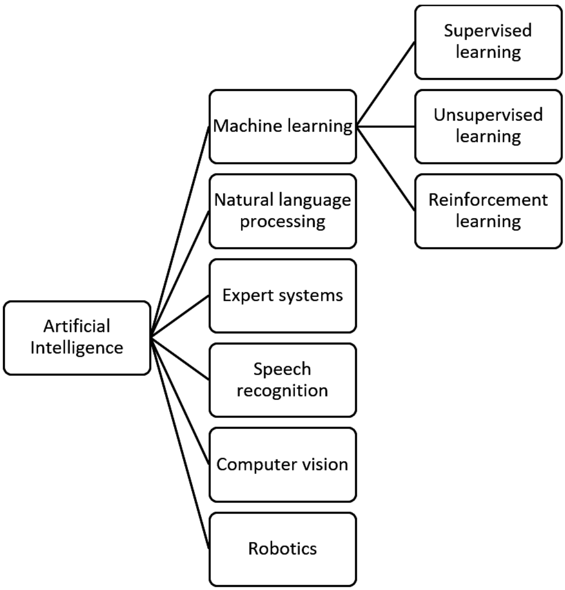

Figure 1
A suggested framework for categorizing AI.

Machine Learning

The basis of AI is the interaction of an agent with the environment. An agent is something that detects and interacts within its environment. For example, a human agent detects the environment with their eyes and ears and interacts with it with their voice and body parts, while a robotic agent detects the environment with cameras and sensors and interacts with it with devices that drive or control his system. When the agent is a computer, this is called Machine Learning (ML). Learning is anything that improves an agent's performance based on his observations and understanding of the world (Russell & Norvig, 2022).

The logical question is, why would we want machines to learn when we know how to program? In their book, Russell and Norvig (2022) mention two main reasons for this. The first reason, as mentioned in the introduction, is that programmers cannot always anticipate every possible scenario beforehand, making it challenging to develop the program with precision. The second is that the programmer might not always have a solution or may not know how to achieve it. An example of this challenge is recognizing elements within images where the programmer may struggle to provide a precise and clear description for the computer, such as identifying a dog, but the computer has no problem doing that, as long as it is provided with sufficient and appropriate data to learn on.

Traditionally, ML has been categorized into three main types, based on the feedback provided to the agent: supervised learning, unsupervised learning, and reinforcement learning (Russell & Norvig, 2022).

When an agent is given pairs of input and output data and learns a mapping that maps the input to the output data, this is called *supervised learning*. For example, in a dataset of ordered pairs of animal images and their names, a pair of a lion's picture and its name "Lion" forms one data entry, demonstrating the correspondence between animal images and their names. The output data in this case is called *label*.

If an agent is given only input data and learns a pattern on its own, this is called *unsupervised learning*. For example, in the dataset of animal images, the agent can identify images of lions and group them together. The agent organizes the images of lions based on its own learned rules from the data, the specifics of which remain unknown to us.

In *reinforcement learning*, the agent receives feedback in the form of rewards or punishments exclusively based on its actions. Considering its widespread usage in intelligent tutors, we will explore it in detail below.

Reinforcement Learning

Wolf (2009) describes Reinforcement learning (RL) as the machine learning technique that is most similar to 'normal' animal and human learning. RL learns based on feedback from the world, whereby feedback refers to rewards and punishments. Based on that feedback, the RL model decides whether to repeat or avoid that specific behaviour in the future. The goal of the agent's learning is to reduce the number of punishments and increase the number of rewards. It may be said that an agent has *learned a behaviour successfully* in the long term, if its interactions lead to rewards.

In observing a person's learning, one can quickly determine what is a reward and what is a punishment for them. For example, a child learning to ride a bike will experience a fall as pain, therefore, a punishment. On the other hand, successfully covering a longer distance will be perceived as an achievement, hence, a reward. The longer the distance they manage to ride, the greater the reward for them. Their long-term goal is to learn to ride the bike without falls, which in the language of RL, encourages maximizing rewards.

How are rewards and penalties documented in the model? For the agent, the reward is usually a scalar value set through interactions with the world. The key is to maximize or minimize this value. In the previous example, every time the child falls off the bike, the scalar value would decrease, and every time the child drives successfully, the scalar value would increase.

Learning a Reinforcement Learning Model

In the process of learning a RL model (Woolf, 2009), two main parts are considered: the *learning agent* and the *world.* We influence the world through our actions, and in return, we receive feedback in the form of rewards or penalties. It is important, therefore, to be aware that we have no new data about the world except the feedback from our actions. This feedback is called the *reward function*, and the choice of action in the current situation is called *policy,* sometimes referred also as the agent function. This process is represented by the graphics in Figure 2.

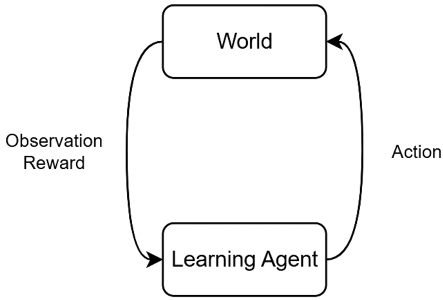

Figure 2
Graphcs of learning a reinforcement learning model.

Policy defines the agent's behaviour at a given time. Policy can also be considered as a mapping between perceived states of the environment and the actions that the agent takes in those states. This mapping can be simple or complex function. It is the core of an RL model.

A reward function is a mapping from the perceived states of the environment to a single number. This number represents the reward or penalty based on its value. The agent's job is to find such a policy that maximizes rewards for long-term behaviour (Woolf, 2009).

Methodology

This chapter outlines the methodologies employed in the research on harnessing AI for personalizing learning. It focuses on the approaches used to investigate the effectiveness of Reinforcement Learning (RL) and Intelligent Tutoring Systems (ITS) in educational settings, the integration of AI in Socio-Emotional Learning (SEL), and the ethical considerations surrounding the use of AI in education. This research aims to contribute to the evolving narrative on AI-driven personalized education by providing a robust understanding of the transformative potential inherent in the integration of AI within educational frameworks.

Research Approach

The research adopts a mixed-methods approach, although it leans more towards theoretical and conceptual analysis. This approach is chosen to provide a comprehensive understanding of the impact and implications of AI in education from a multi-dimensional perspective. The theoretical analysis involves a thorough review of existing literature, encompassing academic journals, case studies, and existing models of AI application in educational settings. This literature review is instrumental in constructing a conceptual framework that underpins the study.

The conceptual analysis is further enriched by a critical examination of case studies and existing implementations of AI in education. This includes an analysis of the deployment of RL and ITS in various educational contexts, their effectiveness, and the challenges encountered. The study also explores the integration of AI in SEL, assessing how AI technologies are being used to support emotional and social learning processes.

In the absence of primary data collection, the study leverages secondary data sources extensively. These sources include published research findings, educational technology reports, and AI implementation reviews. The use of secondary data is crucial in understanding the current state of AI in education, its potential benefits, and the challenges it poses.

Theoretical Framework

The theoretical framework of the study is grounded in the principles of educational psychology, AI, and ML. It draws upon established theories in these fields to analyse how AI can be tailored to individual learning styles and needs. The framework also incorporates insights from the field of cognitive science to understand how AI-driven tools can enhance learning and knowledge retention.

The ethical considerations of AI in education form a critical component of the theoretical framework. This involves an exploration of the balance between technological advancement and ethical responsibility, particularly in the context of data privacy, bias in AI algorithms, and the potential impact on the socio-emotional well-being of learners.

In summary, the methodology of this study provides a comprehensive theoretical and conceptual exploration of AI in education. It aims to offer a nuanced understanding of the potential and challenges of AI-driven personalization in learning environments, contributing to the broader discourse on the future of education in the AI era.

Research on Harnessing AI for Personalizing Learning

Delving further into the domain of AI in education, this section encapsulates a detailed exploration of RL and Intelligent Tutoring Systems (ITS), alongside Individual Student Tutoring, as key mechanisms for personalizing educational approaches. The interplay between RL and ITS unveils a broad spectrum of adaptive educational frameworks, capable of tailoring instructional strategies to meet the nuanced needs of individual learners. The discussion broadens to include Individual Student Tutoring, shedding light on how AI can significantly enhance personalized instructional methodologies, thereby fostering a conducive environment for optimised learning and comprehension. The convergence of these thematic elements showcases a promising pathway towards immediate and personalized feedback mechanisms, which are essential in creating a responsive and engaging educational ecosystem. Through a comprehensive examination of these intertwined aspects, this section aims to unveil the technological and pedagogical innovations that AI brings to the table, and the ensuing implications for enhancing personalized educational experiences. This seeks to provide a robust understanding of the transformative potential inherent in the integration of AI within educational frameworks, thereby contributing to the evolving narrative on AI-driven personalized education.

Reinforcement Learning and Intelligent TutorsIntelligent tutors are a common example of the RL model. The language (terminology) from the previous graphics in Figure 2 may be adapted to this example. In the case of an intelligent tutor, the learning agent represents the teaching agent, i.e., the system or model that teaches the student. The world represents the student. An action represents the teaching activity which the tutor selected. The reward represents the correct answer, and the punishment represents the wrong answer. The model is represented in Figure 3.

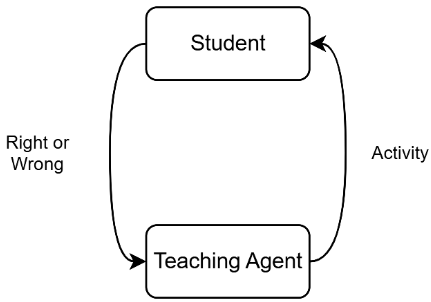

Figure 3
Graphics of learning an intelligent tutor model.

What is interesting about the intelligent tutor model is that there are three core models from which the agent learns. These are the learner model (what is known about the individual learner), the pedagogy model (what is known about teaching), and the domain model (what is known about the subject being learned). The agent is a combination of all three models, enabling personalized learning for the student. The content is tailored to the student's abilities and needs (Luckin et al., 2016).

Individual Student Tutoring

Students in school do not always participate fully, so they do not always learn everything they are required to learn. Often, they must catch up on whatever they missed in school at home, by themselves. To improve or supplement their knowledge, they often turn to various online courses or tutoring. Online courses are affordable and have no time constraints. Their drawback is that they are not tailored to individual students. All students are evaluated based on their knowledge level and then treated the same as others in the group. This is not ideal for students, as they are assessed based only on their knowledge level, not on their learning style or pace of progress.

The type of teaching that adapts to the student's level of learning, learning style, and pace of progress is individual tutoring (Luckin et al., 2016). Tutoring represents the most effective way of learning. However, it has its shortcomings, as it is expensive, making it unaffordable for most students. Additionally, the number of tutors is limited, and if they are available, students must coordinate a time and space that suits both parties.

Here, intelligent tutors come into play as a solution, enabling personalized learning for students with immediate feedback, regardless of the time and space. Intelligent tutors simulate individual tutoring without an individual teacher having to be present.

There are many opportunities for using ITS in educational settings. To name only a few: smartphone ITS for inclusive learning across different geographies, technology-driven teaching transformations, automation in grading systems, personalization in school environments for tailored learning experiences, ITS for enriched distance learning feedback mechanisms, speech-to-text technology for automatic note-taking, and automatic conversational systems for streamlined information accessibility, and so on, which illustrates a wide spectrum of opportunities.

There is also an array of challenges regarding ITS, such as precise representation of student knowledge, data privacy concerns, the indispensable human element in teaching, the complexity in data handling for model training, and difficulties in ML model deployment due to skill and understanding gaps (AlShaikh & Hewahi, 2021).

Immediate and Personalized Feedback

The integration of AI in educational settings heralds a significant advancement in feedback mechanisms, primarily through the provision of immediate and personalized feedback. Using ML algorithms and robust data analytics, AI systems can evaluate individual learner inputs and performance in real-time. This facilitates the immediate delivery of feedback, which is crucial for fostering a conducive learning environment, enabling learners to quickly identify and correct errors, and to reinforce correct understanding and application of concepts. Moreover, the personalized aspect of AI-driven feedback is pivotal, as it tailors the feedback to the unique learning pathways, comprehension levels, and mistakes of each learner. Personalization hence transcends the conventional one-size-fits-all feedback model, offering insights and recommendations that are distinctly relevant to each learner, thereby promoting a more effective and engaging learning experience. The confluence of immediacy and personalization in feedback, orchestrated by AI, is an important step towards a more responsive and individualized educational paradigm, which is instrumental in enhancing learning outcomes and fostering a culture of continuous improvement and learner-centric education.

Research by Maier & Klotz (2022) highlighted the use of students' current knowledge and learning behaviour data for adaptive feedback personalization, with some studies tailoring feedback solely based on student knowledge, providing elaborated feedback messages that offer rich insights into task performance.

Social and Emotional Learning

Social and Emotional Learning (SEL) is an encompassing educational paradigm that fosters the cultivation of cognitive, affective, and behavioural competencies (Kankaraš & Suarez-Alvarez, 2019). It is predicated on the understanding that education transcends academic proficiency, extending to the holistic development of individuals. SEL endeavours to equip learners with the essential skills to comprehend and manage emotions, establish positive relationships, make responsible decisions, and navigate social complexities. The incorporation of SEL within educational frameworks (Berg, et al., 2017) is posited to enrich the learning environment, foster resilience, enhance interpersonal interactions, and contribute to favourable academic outcomes. Its integration is seen as a tool for encouraging a conducive learning ecosystem that enhances not only academic achievement but also the social and emotional skills essential for lifelong success. Through a structured, supportive educational environment, SEL aims to engender a balanced development of individuals, preparing them for the multifaceted challenges and opportunities in their subsequent academic, professional, and personal pursuits.

The intersection of Artificial Intelligence and Social and Emotional Learning

The intersection of AI and SEL presents an exciting opportunity to improve educational methodologies. AI, with its capacity for data analytics and personalized learning experiences, has the potential to significantly increase the efficacy of SEL initiatives. Through analysing behavioural and engagement data, AI can provide insights into learners' emotional states and social interactions, thereby facilitating more nuanced understanding and support for individual socio-emotional development. Moreover, AI-powered educational platforms can be tailored to provide personalized SEL experiences, adapting to the unique needs, emotions, and social contexts of each learner. For instance, AI can help in the early identification of social or emotional challenges faced by learners, enabling timely interventions. Furthermore, AI can assist in creating supportive and engaging learning environments that nurture socio-emotional competencies such as empathy, self-awareness, and interpersonal skills.

However, the infusion of AI into SEL also necessitates a careful consideration of ethical implications, ensuring that the technology is employed in a manner that is sensitive to the diverse socio-emotional needs and contexts of learners. Through thoughtful integration, AI has the potential to significantly increase the reach and impact of SEL, thereby contributing to a more holistic and supportive educational landscape.

Existing research suggests that having AI systems explain their inner workings and algorithms to their potential users can help foster transparency and trust (Conati et al., 2021). There are also suggestions for a moratorium on the utilization of non-epistemic competence components in data-driven AI systems within educational settings. This proposed halt is seen as a necessary step to allow for a comprehensive examination and discussion on the societal and ethical implications of employing AI technologies, particularly those that leverage personal characteristics for personalized learning (Tuomi, 2022).

Conclusion

The exploration of the technological dimension of AI in the educational sector unveils a horizon full of potential and challenges. The seamless merge of AI with educational paradigms has begun to significantly alter the landscape, ushering in an era of personalized, interactive, and enriched learning experiences. The advent of AI-powered feedback mechanisms has introduced a realm of immediate and personalized feedback, contributing to a more responsive and learner-centric educational environment. Furthermore, the intertwining of AI with SEL presents a compelling avenue for fostering holistic learner development, intertwining cognitive growth with emotional and social acuity.

The journey of AI from a speculative conjecture to a tangible reality, has been marked by pivotal milestones, each contributing to the unfolding narrative of AI in education. The examination of historical and contemporary instances illustrates a trajectory marked by continual evolution, driven by both technological advancements and an expanding understanding of the multifaceted nature of learning.

The ethical considerations related with AI's integration in educational environment warrant a thorough examination to ensure a judicious and inclusive application. Moreover, as AI continues to evolve, so too will its potential applications within education. Future work should aim to explore the longitudinal impacts of AI on educational outcomes, delve into the ethical and privacy implications, and investigate the potential for emerging AI technologies to further augment SEL and other educational paradigms. Additionally, the design and evaluation of AI systems that are sensitive to the diverse socio-cultural contexts within which education transpires, remain a crucial challenge. The potential for cross-disciplinary collaboration, bringing together the insights from educationists, psychologists, technologists, and policymakers, presents a rich avenue for holistic research and implementation strategies.

The continual evolution of AI technologies, coupled with rigorous research and ethical considerations, harbours the potential to significantly enrich the educational domain, creating a beneficial learning environment that nurtures not only academic growth but also the holistic development of learners.

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Intersecting Evaluations: Digital Competence and AI Attitudes among Students

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Abstract

This study explores the effectiveness of the SETCOM intervention in improving the digital competencies of students (pre-service teachers), using the DigComp 2.1 criteria. In the study involving 82 pre-service K-12 teachers from the University of Maribor, notable progress was observed across all DigComp 2.1 areas after completing two out of the three four-hour segments of the intervention. The greatest progress was observed in Information and Data Literacy, while the lowest progress was in Digital Content Creation. It is important to note the medium-level progress in six specific sub-competencies, and a significant advancement in the sub-competence of Browsing, Searching, and Filtering Data. The results suggest the SETCOM intervention is effective in enhancing most digital competencies of future teachers. Additionally, no significant differences in progress across DigComp 2.1 areas and no disparities in digital competence development based on gender were detected. This positive outcome reflects that the intervention consistently followed the principle of treating everyone fairly. Overall, the connection between digital competencies and social-emotional competencies was highlighted as important. Recognising this connection can help shape future teaching strategies, ensuring that teacher training programmes focus on both digital and social-emotional skills.

Keywords: digital competence areas, holistic competence development, gender gap analysis, AI literacy, SEL

Introduction

Nowadays, with the changes in society and hence different learning needs, there is a necessity for redefining teacher competencies. In this respect, there is a need for teachers who can design enriched and innovative learning environments that enable students to explore by using technology. In terms of technology integration, research on the assessment of educational training combined with digital competence frameworks is required (Falloon, 2020). Lim et al. (2021) suggest implementing more intervention programmes and training to upskill teachers' digital competence. Therefore, it is necessary to explore in general the changes in pre-service teachers' digital competencies as an effect of such intervention programmes. Reisoğlu and Çebi (2020) evaluated an intervention programme, in which the DigComp framework was used as the foundation, and which aimed to develop and support the digital competencies of pre-service teachers in Turkey. They used the DigComp and DigCompEdu frameworks to analyse data. Results of their analysis show that even after training, there is a lack of comments on some of the sub-competencies such as *Citizen participation online*, *Integrating and re-elaborating digital content*, *Innovation and use of digital technology in a creative way*, *Protection of the environment*, Reflective practice, *Guidance*, and *Differentiation and personalisation*.

At the University of Maribor, Slovenia, an intervention programme SETCOM has been implemented to cultivate artificial intelligence (AI) literacy and social-emotional learning (SEL) of future teachers. This initiative educates pre-service teachers on both the technical aspects of AI and the fundamentals of social and emotional learning, preparing them to integrate these elements into the evolving educational sphere. The focus of the SETCOM project was on AI literacy, which falls under the broader category of information and data literacy. The curriculum merges learning AI technological, didactical and human dimensions, with activities aimed at enhancing empathy, emotional management, and decision-making. The training includes practical AI tools engagement and SEL scenarios application, equipping participants with a comprehensive skillset to foster a well-rounded learning environment for students. In this study we report the impact of the SETCOM programme on digital competence among pre-service teachers.

Digital Competence of Educators

Until now, several frameworks and models have been used to study digital competence. DigComp is one of the most current and extensive frameworks developed. Version 2.0 is an improvement of DigComp 1.0, with new requirements taken into consideration to meet the fast pace of development, while DigComp 2.1 adds another dimension and examples of use on how each competence can be applicable in different ways and for different purposes (Carretero Gomez et al., 2017). The recently developed DigComp 2.2 framework provides even more examples from the field of new and emerging technologies, such as AI-driven systems (Vourikari et al., 2022). The DigComp framework consists of five competence areas: Information and Data Literacy, Communication and Collaboration, Digital Content Creation, Safety, and Problem-solving. The successful inclusion of technology into teaching relies on educators' digital competencies as outlined by DigComp, a comprehensive framework encompassing areas like Information and Data Literacy, Communication and Collaboration, Digital Content Creation, Safety, and Problem-solving (Carretero Gomez et al., 2017).

There are numerous studies reflecting upon the DigComp 2.1 competence framework of educators (e.g. Lim et al., 2021; Núñez-Canal et al. 2022, for review see Bilbao Aiastui et al., 2021). For instance, the results for secondary school teachers in Malaysia suggest that digital competence, according to DigComp 2.1, is highly significant in influencing workforce agility (Lim et al., 2021), where teachers' workforce agility refers to a flexible and well-trained workforce that can easily and quickly adapt to new situations and opportunities (Muduli & Pandya, 2018).

The European Framework for the Digital Competence of Educators (DigCompEdu) on the other hand, categorises educators' digital competencies and focuses only on the knowledge, skills and attitudes related to the use of digital technologies in educational environments (Redecker C. , 2017). The DigCompEdu lists competencies organised into six areas: Professional Engagement, Digital Resources, Teaching and Learning, Assessment, Empowering Learners, and Facilitating Learners' Digital Competencies. After carrying out a systematic literature review and checking the results obtained, as far as the areas of DigCompEdu are concerned, Bilbao-Aistaui et al. (2021) report that the subarea (1.3) Reflective Practice has not been cited in any article, and that areas (5) Learner's Empowerment, and (6) Facilitating Students' Digital Competence, are those least referred to in higher-education settings for university professors.

Pre-service teachers' digital competencies stand out from those of experienced educators and other individuals. Their uniqueness stems from their primary focus on using digital technology specifically for educational purposes, combined with the fact that they lack the practical teaching experience that experienced educators possess. Krumsvik (2011) defines digital competence for pre-service teachers as proficiency in using digital technologies with good pedagogic-didactic judgments and awareness of the implications of these technologies for learning strategies and the digital culture of students. Given this intricate definition, it's evident that in the Slovenian context, achieving such expertise is challenging. This is primarily because future teachers often lack substantial experience in real-world educational settings.

In this study, we used DigComp 2.1 since the participants were still in the process of transforming into teachers and did not have enough classroom experiences to reflect upon the DigCompEdu questionnaire. AI was addressed separately, and therefore DigComp 2.2 would not have provided new insights. The DigComp 2.1 competencies are grouped into five competence areas, as presented in Table 1.

Table 1
DigComp 2.1 competences

Competence Area	Competences
CA 1 Information and data literacy	C1.1 Browsing, searching, and filtering data, information and digital content
	C1.2 Evaluating data, information, and digital content
	C1.3: Managing data, information, and digital content
CA 2 Communication and collaboration	C2.1 Interacting through digital technologies
	C2.2 Sharing through digital technologies
	C2.3 Engaging in citizenship through digital technologies
	C2.4 Collaborating through digital technologies
	C2.5 Netiquette
	C2.6 Managing digital identity
CA 3 Digital content creation	C3.1 Developing digital content
	C3.2 Integrating and re-elaborating digital content
	C3.3 Copyright and licences
	C3.4 Programming
CA 4 Safety	C4.1 Protecting devices
	C4.2 Protecting personal data and privacy
	C4.3 Protecting health and well-being
	C4.4 Protecting the environment
CA 5 Problem-solving	C5.1 Solving technical problems
	C5.2 Identifying needs and technological responses
	C5.3 Creatively using digital technologies
	C5.4 Identifying digital competence gaps

The DigComp 2.2 (Vourikari et al., 2022) update also addresses the topic of citizens' interaction with AI systems and does not focus on knowledge about AI per se. Annex 2 focuses specifically on citizens interacting with AI systems in three domains: knowledge, skills, and positions domain. This framework was used in the SETCOM project to develop competencies in all three domains. In the knowledge domain, we addressed the awareness of what AI systems do and do not do and the understanding of AI systems' benefits, limitations, and challenges. In the skills domain, we reinforced the idea of using, interacting with, and providing feedback to AI systems as an end-user. In the domain of the position, we discussed human actions and control, reinforced critical but open attitudes, and addressed ethical aspects of use.

Digital competencies in diverse educational contexts

While the primary focus of this article is on educators and pre-service teachers, it's also essential to recognise that the need for research and consequently improving digital competencies extends beyond the realm of formal education. Various formal and informal education settings, such as general training programs and courses for acquiring licenses or certificates, also require a robust foundation in digital skills. In today's interconnected world, the demand for digital literacy spans across diverse learning environments, making it imperative for individuals in various educational contexts to enhance their digital competencies and lately also in AI literacy.

Understanding the specific needs for enhancing digital competencies in these diverse educational contexts, for example for vocational education and training (VET) is crucial. Exploring digital competencies within VET, recent research provides some insights into this. For example, trainees in commercial vocational education exhibit diverse digital competencies, revealing three distinct profiles influenced more by school leaving certificates than gender (Findeisen et al., 2022). Barboutidis and Stiakakis (2023) reported that factors such as age, education level, specialisation, and technology use significantly influence specific DigComp areas among Vocational Training Institute students. On the other hand, digital competence levels among Swiss VET teachers are consistent, with attitude towards technology, digital tool use frequency, and workload identified as influential factors (Cattaneo et al., 2022). How VET teachers intend to use digital tools is researched in (Antonietti et al., 2022) by the technology acceptance model. Finally, diverse digital competencies among first-year students in business-focused cooperative study programs, emphasising the need for tailored support in developing students' digital competencies are identified (Schulze Heuling et al., 2021). In summary, these studies collectively underscore the multifaceted nature of digital competencies within vocational education, emphasising the importance of considering personal and institutional factors for effective digital literacy development.

The SETCOM Intervention programme

Education is transforming also due to modern technologies, including artificial intelligence (Kim et al., 2021), which holds great untapped educational potential. AI allows machines to mimic human-like learning and reasoning (European Parliament, 2023). In education, AI offers adaptive instruction and individualized learning experiences, leading to improved student performance (Chiu et al., 2023). However, its integration faces challenges such as technical limitations and ethical concerns (Zhai et al., 2021).

SETCOM aims at developing synergies between AI literacy and social-emotional competencies among future teachers. Social and emotional competence is developed through social-emotional learning (SEL). This is a process of developing skills, attitudes, and values necessary for acquiring social and emotional competence (Elias et al., 1997). The intervention programmes that include SEL positively affect students' academic performance (Durlak et al., 2011). We assert that the interplay between AI literacy and SEL has the potential to enhance the digital competencies of pre-service teachers. This is because SEL provides a deeper understanding of AI, underscoring the need for a human-centred approach and the role of teachers' attitudes. As we look to the future, the emphasis on well-being in the digital world – covering physical, emotional, social, and ethical dimensions – demonstrates the intertwined relationship between AI literacy and SEL, signifying a transformative direction for education. The aim of the SETCOM intervention is therefore to create a comprehensive approach to promote AI's responsible and effective use in education while fostering positive attitudes towards this technology among educators and learners.

The content of the intervention has been divided into three main strands: ABOUT, WITH, and FOR. The strands are based on the recommendations of the EU Commission in Artificial Intelligence and Education (Holmes et al., 2022) and DigComp 2.2. interacting with AI domains (knowledge, skills, and positions).

The first strand, ABOUT, covers basic information on AI systems and SEL. It includes definitions and basic classifications (e.g., broad and narrow AI), and models (e.g., CASEL). This strand involves improving the knowledge and skills of pre-service teachers about AI, covering AI techniques (e.g., machine learning) and AI technologies (e.g., natural language processing), together with statistics and coding. This strand is sometimes referred to as *AI literacy: the technological dimension* in the context of literature on AI in education (Holmes et al., 2022).

The second strand, WITH, focuses specifically on the use of AI and SEL in pedagogical situations. We show different examples of tools (e.g., ChatGTP, Plutching wheel) and situate them in educational situations. Topics involve the use of AI tools in teaching and learning and include: the use of AI to directly support learners (e.g., intelligent tutoring systems, dialogue-based tutoring systems, automated writing assessment, learning networks, chatbots); the use of AI to support learners with disabilities; the use of AI to support administrative systems (such as enrolment, assessment, timetables, etc.), and the use of AI to directly support teachers (e.g., smart editing of learning materials). We also included the aspect of *using of AI for learning about learning.* This area is commonly known as learning analytics or data mining in education. Although it is not strictly AI, the use of AI for learning about learning involves the analysis of similar data and similar analytical techniques to those used by 'learning by AI' tools. Except that in this case, the data is used to learn about how students learn about the progress of learning, or about which learning models are effective.

The third strand, the FOR strand, focuses on the future. We think about what skills will be needed in the future (e.g., prompt engineering, communicating with chat bots), with a particular focus on the ethics of AI. Preparing for a life with AI involves developing competencies to ensure that all citizens are prepared for the potential impact of AI on their lives. It is important to develop competencies that go beyond mere enthusiasm for AI, but also understand issues such as the ethics of AI, data bias, surveillance and the potential impact on citizens and their workplaces. Preparation for AI could be integrated into learning about AI; it is only separated to give it the attention it deserves. This strand is sometimes referred to in education literature as *AI literacy: the human dimension* (Holmes et al., 2022).

In the intervention, each strand consists of four lessons, half of them designed as lectures and the other half as workshops. The intervention is still in progress. Until November 2023, we have implemented the first two strands, ABOUT and WITH. From the initial assessment of the SETCOM intervention, some results have emerged, with only certain findings appearing promising. Lipovec et al. (2023) indicate that the pre-service teachers generally held positive views on AI and demonstrated favourable beliefs about SEL. Notably, potential relationships emerged between their attitudes towards AI and specific elements of SEL. For instance, a pre-service teacher's willingness to address students' social and emotional needs might correlate with their receptiveness to incorporating AI in the classroom. However, a contrasting view is presented by a more focused digital evaluation by Lipovec and Flogie (2023). Their findings suggest that, at this initial stage, the attitudes of SETCOM pre-service teachers towards AI, as measured by the General Attitudes Towards AI Scale (GAAIS), were less positive than those of the general population. Considering that pre-service teachers play a central role in developing learners' competencies; it is essential for them and their learners to have positive or at least neutral attitudes towards AI. This highlights the strategic decision of the SETCOM project to emphasize not just digital skills but also intra- and interpersonal competencies, suggesting that cultivating positive attitudes in these areas is fundamental for comprehensive digital competence development.

As stated before, there is a growing call for research to understand how we can better merge tech-focused education with frameworks that assess digital competence (Falloon, 2020). It is therefore time to dive into *how* these training programmes impact the digital skills of our upcoming educators. This is why we are turning our attention to the effects of intervention programmes like the SETCOM programme at the University of Maribor: so that we can truly understand how such interventions shape the digital know-how of future teachers.

Methodology

Research Design

The following research questions have been set forth.

1. To what extent does the SETCOM intervention impact the digital competencies of future teachers as evaluated by the DigComp 2.1 criteria?
2. How does the impact of the SETCOM intervention vary across different areas of the DigComp 2.1?

To address these questions, methods of quantitative empirical pedagogical research in a longitudinal context have been used. The initial state data was collected between October 2022 and January 2023, while data for the intermediate state (the state after implementing the strands ABOUT and WITH) was collected between February 2023 and July 2023. For each pre-service teacher, the intervention spanned roughly throughout 5–7 months. This duration varied based on whether the subject, under which the intervention took place, was part of the winter or the summer semester.

Data obtained from questionnaires were analysed with IBM SPSS Statistics 27.

Instrument

The anonymous questionnaire consisted of three sections of questions:

a) demographics,
b) Artificial Competence Literacy: two knowledge self-reporting questions, General Attitudes towards AI Scale – GAAIS (Schepman & Rodway, 2020), Attitudes toward the ethics of artificial intelligence – AT-EAI (Jang et al., 2022) and Competence Framework for Citizens DigComp 2.1 (Carretero Gomez et al., 2017); and
c) questions about assessing participants' beliefs about social and emotional learning – SEL (Brackett et al., 2012).

Questions from section (b) DigComp 2.1 were answered by agreeing with the proficiency levels on an eight-level scale, measured with complexity of tasks and autonomy: (1) simple tasks, with guidance, (2) simple tasks with autonomy, with guidance when needed, (3) well-defined and routine tasks, and straightforward problems, on my own, (4) tasks, and well-defined and non-routine problems independent, according to my needs, (5) different tasks and problems, guiding others, (6) most appropriate tasks, able to adapt to others in a complex context, (7) resolve complex problems with limited solutions, integrate to contribute to the professional practice and to guide others, (8) resolve complex problems with many interacting factors, propose new ideas and processes to the field.

In this report, only longitudinal results for the pre-service teachers' self-reported DigComp 2.1 competencies were considered.

Sample

The participants in the intervention were kindergarten and elementary students, pre-service kindergarten, elementary and secondary teachers, in-service kindergarten, elementary secondary and high school teachers, and administrative workers in educational institutions. This study focuses only on the pre-service teachers' responses. The questionnaire was answered by 82 participants who are pre-service teachers at the University of Maribor and currently studying in K-12 teaching programmes. As shown in Table 2, the sample consisted of 70 females (85.4 %) and 12 males (14.6 %), aged between 20 and 25 years, with an average age of 21.6 years.

Table 2
Sample structure

		f	f%
Gender	Male	12	14.6
	Female	70	85.4
Age	20	22	27.5
	21	17	21.3
	22	24	30.0
	23	12	15.0
	24	5	6.3
	25	2	2.5

Limitations

This study has four main limitations. First, K-12 teachers are a heterogeneous group, e.g., future computer science teachers differ from future primary teachers. In our sample, primary pre-service teachers prevailed, followed by social science teachers, and less than one-tenth of the sample consisted of future STEM teachers. Second, DigComp 2.1 is designed for the general population and does not specifically address teaching professions. And third, only part of the results of a more extensive study is analysed, lowering the data triangulation level. The last limitation is a gender unbalanced sample that can lead to misleading results when considering gender differences.

Results

In Table 3, the results of assessing the progression of participants' digital competence knowledge are presented. Pre-service teachers self-evaluated each competence before the implementation of the first strand ABOUT and after the implementation of the second strand WITH. The differences in their ratings were calculated, along with their averages (M), standard deviations (SD) and effect sizes (Cohens' d).

Additionally, the number of participants for each competence whose scores on specific competence (e.g. C1.1) increased (Positive), decreased (Negative), or remained unchanged (Zero), was determined. Averages for competence area were calculated as averages of scores for specific competence (e.g. the average for CA 1 is an average of C1.1, C1.2 and C1.3). For the competence area, we also counted how many participants had positive/negative/zero averages of all the sub-competencies in this area. In Table 3 the competence area results are recorded in bold.

Table 3
DigComp2.1 Progress

[a]	M	SD	Cohens' d	Positive		Negative		Zero	
				f	f%	f	f%	f	f%
C1.1	0.80	2.34	0.34	43	52.4	23	28.0	16	19.5
C1.2	0.70	2.21	0.32	43	52.4	22	26.8	17	20.7
C1.3	0.61	2.13	0.28	45	54.9	24	29.3	13	15.9
CA 1[b]	**0.70**	**2.02**	**0.35**	**50**	**61.0**	**24**	**29.3**	**8**	**9.8**
C2.1	0.40	2.02	0.19	38	46.3	23	28.0	21	25.6
C2.2	0.70	1.93	0.36	42	51,2	19	23.2	21	25.6
C2.3	0.38	1.77	0.21	38	46.3	25	30.5	19	23.2
C2.4	0.40	1.84	0.22	39	47.6	22	26.8	21	25.6
C2.5	0.73	2.33	0.31	43	52.4	20	24.4	19	23.2
C2.6	0.57	2.14	0.27	40	48.8	29	35.4	13	15.9
CA 2[b]	**0.53**	**1.62**	**0.33**	**50**	**61.0**	**31**	**37.8**	**1**	**1.2**
C3.1	0.48	2.06	0.23	44	53.7	28	34.1	10	12.2
C3.2	0.41	2.06	0.20	40	48.8	27	32.9	15	18.3
C3.3	0.38	2.02	0.19	37	45.1	27	32.9	18	22.0
C3.4	-0.37	2.85	-0.13	26	31.7	26	31.7	30	36.6
CA 3[b]	**0.23**	**1.77**	**0.13**	**42**	**51.2**	**33**	**40.2**	**7**	**8.5**
C4.1	0.22	2.18	0.10	36	43.9	30	36.6	16	19.5
C4.2	0.13	2,02	0.06	33	40.2	31	37.8	18	22.0
C4.3	0.29	1.82	0.16	35	42.7	31	37.8	16	19.5
C4.4	0.35	1.86	0.19	30	36.6	25	30.5	27	32.9
CA 4[b]	**0.25**	**1.54**	**0.16**	**38**	**46.3**	**33**	**40.2**	**11**	**13.4**

C5.1	0.34	2.14	0.16	36	43.9	30	36.6	16	19.5
C5.2	0.45	2.31	0.19	37	45.1	29	35.4	16	19.5
C5.3	0.57	2.29	0.25	39	47.6	30	36.6	13	15.9
C5.4	0.34	2.59	0.13	37	45.1	23	28.0	22	26.8
CA 5[b]	**0.43**	**2.00**	**0.22**	**39**	**47.6**	**34**	**41.5**	**9**	**11.0**

[a] Sub-competencies and competence areas are denoted according to Table 1.

[b] The competence area results are recorded in bold.

We have introduced a Progress-Index, which is the ratio of the number of prospective teachers who achieved a positive average in a competence area to the number of students who scored a negative average in the same area. The higher the Progress-Index the better the improvement in the competence area for our sample. Our findings are as follows: CA 1 Progress-Index is 2.08, for CA 2 it is 1.61, for CA 3 it is 1.27, for CA 4 it is 1.15 and for CA 5 the Progress-Index is 1.14. The Progress-Index decreases across competency areas, being highest for CA 1 and lowest for CA 5.

We examine two aspects of the global results: the Progress Index and the Average Score. The Progress-Index clarifies changes from the perspective of a participant, indicating where an increase, decrease, or no change in competency area improvement was observed. The Average Score for each competency area (see Table 3, Average Score – AvScore, in bold) indicates *the magnitude* of the increase, decrease, or no change on the 8-level DigComp scale.

The Average Score was computed for each participant individually, finding that this average was positive for 49 (60 %) pre-service teachers, indicating an overall improvement in their digital competencies, while it was negative for 33 (40.2 %) pre-service teachers.

As shown in Table 3, an improvement in all DigComp 2.1 areas was recorded. The highest progress of 0.70 (on 1–8 level scale) was achieved in CA 1 *Information and Data Literacy*, followed by 0.53 improvement in CA 2 *Communication and Collaboration*, and 0.43 in CA 5: *Problem-solving*. Lower increases were observed for CA 3 *Digital Content Creation* (0.23) and for CA 4 *Safety* (0.25).

Among the sub-competencies, all but one showed progress. Specifically, a -0.37 decline was noted in C3.4 *Programming*.

Two sub-competencies demonstrated minimal improvement, with progress scores ranging between 0 and 0.24. These are C4.1 *Protecting Device* and C4.2 *Protecting Personal Data and Privacy*. A modest improvement, with progress mean scores between 0.25 and 0.49, was observed in the following eleven sub-competencies: C2.1 *Interacting through Digital Technologies*, C2.3 *Engaging in Citizenship through Digital Technologies*, C2.4 *Collaborating through Digital Technologies*, C3.1 *Developing Digital Content*, C3.2 *Integrating and Re-Elaborating Digital Content*, C3.3 *Copyright and Licences*, C4.3 *Protecting Health and Well-Being*, C4.4 *Protecting the Environment*, C5.1: *Solving Technical Problems*, C5.2 *Identifying Needs* and *Technological Responses*, and C5.4 *Identifying Digital Competence Gaps*.

A medium improvement, indicated by progress mean scores between 0.50 and 0.74, was evident in six sub-competencies: C1.2 *Evaluating Data*, *Information, and Digital Content*, C1.3 *Managing Data, Information, and Digital Content*, C2.2 *Sharing through Digital Technologies*, C2.5 *Netiquette*, C2.6 *Managing Digital Identity*, and C5.3 *Creatively Using Digital Technologies*.

Lastly, a substantial improvement, marked by progress mean scores exceeding 0.75, was identified in the sub-competence C1.1 *Browsing, Searching, and Filtering Data, Information, and Digital Content*.

Using Friedman's Analysis of Variance by Ranks (also referred to as Friedman's ANOVA), no statistically significant differences were observed in improvements based on the DigComp 2.1 competence areas (Q = 1.1753, P = 0.781). Further exploration through post hoc analyses revealed that for CA 1 when compared with other areas (CA 1 – CA 2: Q = 0.189, P = 0.444; CA 1 – CA 3: Q = 0.274, P = 0.266; CA 1 – CA 4: Q = 0.226, P = 0.361; CA 1 – CA 5: Q = 0.073, P = 0.767), there were no notable differences in comparisons involving Competence Area 1. Similarly, comparisons involving Competence Area 2 with the other areas (CA 2 – CA 1: Q = 0.189, P = 0.444; CA 2 – CA 3: Q = 0.085, P = 0.730; CA 2 – CA 4: Q = 0.037, P = 0.882; CA 2 – CA 5: Q = -0.116, P = 0.639) also indicated no significant differences. Comparisons involving Competence Area 3, Competence Area 4 and Competence Area 5 showed the same results (CA 3 – CA 4: Q = -0.049, P = 0.843, CA 3 – CA 5: Q = -0.201, P = 0.415, CA 4 – CA 5: Q = -0.152, P = 0.537). Uniform development across competence areas was evident across all other paired comparisons, confirming that the progression in digital competencies was balanced with no significant lead or lag among the areas.

As digital competenices are considered to be prone to gender gap, we also examined that aspect. We report averages (M) and standard deviations (SD) in self-reported differences in competencies before and in the middle of SETCOM Intervention programme for 12 males and 70 females separately.

Table 4
Development in sub-competencies according to gender.

Comp[a]	Male M	Male SD	Female M	Female SD	$\chi^2_{(lr)}$	P
C1.1	0.75	0.687	0.81	0.281	14.697	0.258
C1.2	0.08	0.645	0.80	0.263	14.262	0.219
C1.3	0.50	0.544	0.63	0.261	14.129	0.167
CA 1[b]	**0.44**	**0.567**	**0.75**	**0.244**	**19.714**	**0.787**
C2.1	0.17	0.386	0.44	0.254	16.199	0.094*
C2.2	0.17	0.297	0.79	0.243	17.322	0.044**
C2.3	0.42	0.434	0.37	0.217	4.216	0.755
C2.4	0.58	0.452	0.37	0.226	10.586	0.305
C2.5	0.42	0.793	0.79	0.271	13.877	0.309
C2.6	0.58	0.783	0.57	0.246	10.687	0.382
CA 2[b]	**0.39**	**0.458**	**0.55**	**0.195**	**25.974**	**0.803**
C3.1	0.92	0.633	0.40	0.244	16.460	0.087*
C3.2	0.17	0.534	0.46	0.251	13.609	0.255
C3.3	-0.42	0.499	0.51	0.245	12.768	0.173
C3.4	-0.50	0.57	-0.34	0.357	15.506	0.344
CA 3[b]	**0.04**	**0.457**	**0.26**	**0.216**	**25.498**	**0.548**
C4.1	0.50	0.500	0.17	0.270	9.232	0.600
C4.2	-0.42	0.753	0.23	0.228	10.406	0.319
C4.3	1.17	0.661	0.14	0.204	5.777	0.672
C4.4	0.92	0.633	0.26	0.214	15.085	0.129
CA 4[b]	**0.54**	**0.533**	**0.20**	**0.178**	**12.243**	**0.933**

C5.1	0.25	0.446	0.36	0.267	4.852	0.901
C5.2	-0.25	0.463	0.57	0.287	14.369	0.157
C5.3	0.67	0.396	0.56	0.290	19.265	0.037**
C5.4	-0.25	0.653	0.44	0.316	6.722	0.821
CA 5[b]	**0.10**	**0.314**	**0.48**	**0.253**	**34.753**	**0.145**

[a] Sub-competencies and competence areas are denoted according to Table 1.

[b] The competence area results are recorded in bold.

There were no differences according to gender in either of the competence areas (CA 1 $\chi^2_{(lr)}$ = 19.714, P = 0.787; CA 2 $\chi^2_{(lr)}$ = 25.974, P = 0.803; CA 3 $\chi^2_{(lr)}$ =25.498, P = 0.548; CA 4 $\chi^2_{(lr)}$ =12.243, P = 0.933; CA 5 $\chi^2_{(lr)}$=34.753, P = 0.145). However, statistically significant differences were observed at the 5 % significance level for sub-competences C2.2 *Sharing through digital technologies* (favouring female) and C5.3 *Creatively using digital technologies* (favouring male), and at the 10 % trend level for sub-competencies C2.1 *Interacting through digital technologies* (favouring female) and C3.1 *Developing digital content* (favouring male).

Discussion

Overall results reveal that 49 pre-service teachers, comprising 60 % of the sample, showed an increase in digital DigComp competencies, suggesting an enhancement in their digital skills. Conversely, a small decrease was observed for 33 pre-service teachers, representing 40.2 % of the sample, indicating a decline in their digital competencies. It is crucial to await the completion of the intervention programme before drawing definitive conclusions about the observed increase/decrease in some participants' digital competencies. The final third of the programme targets namely specific competencies that are currently showing a decrease. If this decline persists by the end of the programme, further research will be necessary to understand the underlying reasons. This should include a close examination of the characteristics of the pre-service teachers who exhibit this trend to identify any common factors or experiences that may contribute to the decrease. Additionally, decrease can potentially be linked to the phenomenon known as the Dunning-Kruger effect. Kruger and Dunning (1999) conducted research among psychology students to assess their ability to evaluate their own competencies and performance. The findings of their study revealed that students who performed poorly tended to significantly overestimate their abilities, while the more competent students often underestimated their own abilities. This finding has since been confirmed in various other fields. The discovery itself is not as unusual as the realisation that in many cases, people are not aware of their inaccurate self-assessments; instead, it is often the case that less competent individuals have a high degree of confidence in their knowledge (Dunning, 2014). Similarly, it can be inferred that the pre-service teachers in SETCOM programme might have initially overestimated their digital competencies, lacking the necessary knowledge to accurately assess themselves. However, after completing the second third of the programme, they were better at self-assessment, having gained more knowledge and thus able to place their competencies more objectively.

The effect size, as measured by Cohen's d, approaches Hattie's hinge point (Hattie, 2023) of 0.40 for CA 1 and CA 2, indicating a possibility of a promising result at the end of the SETCOM programme. The ordering of the Progress-Index from Competence Area 1 *Information and Data Literacy* to CA 5 *Problem-solving* may be attributed to several factors. Firstly, Information and Data Literacy is often the foundational aspect of digital competence, typically emphasised early in educational curricula, leading to higher proficiency among students (Çebi & Reisoğlu, 2019). Conversely, Problem-solving requires the application of digital skills in complex, real-world scenarios, which may not be as extensively covered or practised in educational settings. Additionally, as educators move from theoretical knowledge to practical application, the complexities of navigating digital safety and creative problem-solving could present harder learning challenges (Carretero Gomez et al., 2017), which is reflected also in the lower Progress-Index scores.

The intermediate competencies, *Communication and Collaboration*, *Digital Content Creation*, and *Safety*, present varying challenges that could influence the Progress-Index. Communication and Collaboration are central to many educational activities, potentially receiving more attention and thus yielding higher progress (Napal et al., 2018). Digital Content Creation, while integral, may be less familiar for students, requiring not only technical skills but also creativity and design thinking, which can be more demanding to develop (Mouza et al., 2018). Safety, although crucial, might not exhibit a high progress index if its principles and practices are not thoroughly integrated into the learning process, leading to less confidence and competence among students in this area according to study results from Çebi et al. (2022).

The greatest progress was observed in Competence Area 1 *Information and Data Literacy*, on average the progress on an 8-level competence was 0.70. This is expected since the SETCOM project addressed AI literacy, which is a subset of information and data literacy. AI literacy is widely recognised as a new set of competencies that enable people to use AI effectively and ethically in their daily lives. One of the aims of AI literacy education for primary schools is to introduce children to the basic concepts of AI/computing and to encourage them to discover the link between AI applications and the basic concepts. For example, researchers have introduced children to AI concepts through high-order thinking activities such as creating digital stories, running the Turing test with intelligent agents, creating chatbots and reasoning algorithms, and building applications through block-based programming (Ng et al., 2021). A similar approach was taken in the SETCOM project, where unplugged AI concepts (Lindner & Seegerer, 2022) were introduced through a playful and exploratory approach.

The findings of this study align mostly with those of Reisoğlu and Çebi (2020). In the SETCOM intervention programme, courses were designed to show lecturers as role models for future teachers. These courses combined theoretical knowledge with practical, hands-on experience, mirroring the “learning by doing” approach noted by Reisoğlu and Çebi (2020). They developed a course grounded in the DigComp framework, targeting the enhancement of digital competencies among pre-service teachers. This training spanned over the period of a week, providing participants with 70 hours of instruction. They documented progress in all three sub-competencies within the CA 1 competence area, though their study, being qualitative in nature, did not provide quantitative data. By contrast, the SETCOM course, which lasted for 8 hours until data was gathered for this study, can supplement their findings with quantitative data. Specifically, results show medium progress in two sub-competencies (C1.2 and C1.3), and substantial progress in one competence (C1.1). These results are in line with a study by Çebi and Reisoğlu (2019), which highlighted that digital competence training aided pre-service teachers in developing mostly their skills related to information search strategies, accessing relevant data, assessing the credibility of sources, and efficiently organising and storing information.

In the CA 2 domain, which covers *Communication and Collaboration*, the findings of this study show that future teachers exhibited an average improvement of 0.53 on an 8-level competence. Positive mean progress scores were observed across all sub-competencies, with three (C2.1, C2.3 and C2.4) demonstrating modest progress and the other three (C2.2, C2.6 and C2.5) showing medium advancements. Interestingly, Reisoğlu and Çebi (2020) documented progress in five sub-competencies but found no advancement in the C2.3 sub-competence: *Engaging in Citizenship through Digital Technologies*. A review of the literature, including the work by Napal et al. (2018), reveals that efforts within the CA 2 domain often emphasize the C2.1 and C2.2 sub-competencies. Our belief is that C2.3 was effectively addressed during the SETCOM intervention due to synergies with social-emotional competencies. As outlined by Marín-López et al. (2019), modern citizens need to proficiently manage their emotions. Competencies like morality, empathy, and emotional intelligence, which play pivotal roles in informal face-to-face communications, are also emerging as vital for online interpersonal interactions.

In the CA 3 domain related to *Digital Content Creation*, the results of this study indicate a modest average improvement of 0.23 among future teachers. Of the evaluated sub-competencies, three displayed modest progress (C3.1, C3.2 and C3.3). Notably, the only sub-competence that demonstrated a decline was C3.4 *Programming*, which is the fourth sub-competence within this domain. Interestingly, the study by Reisoğlu and Çebi (2020) showed that participants didn't enhance their knowledge and skills in C3.2. However, they did register improvements in all other sub-domains, including programming. Studies have pinpointed the challenges primary educators face in integrating computational thinking related to programming (e.g., Kong at al., 2020). These challenges often arise from a lack of academic background in computer science or related fields, a shortage of confidence in teaching programming, or the perceived absence of sufficient support (Mouza et al., 2018). While intensive workshops are recognised as a popular method for boosting teacher capabilities in computational thinking related to programming, Darling-Hammond et al. (2017) stress the importance of development based on extended and active engagement. In the SETCOM intervention, time was evenly divided between lectures and workshops. This arrangement, while appearing balanced, did not provide participants with adequate opportunity to explore programming. Even though they were introduced to block-programming tools like Scratch, they could not truly experiment with them without additional personal involvement. Given these observations, a beneficial adjustment to the SETCOM intervention would be to extend the course duration. By dedicating more time to interactive workshops, participants could actively engage and practice more effectively, especially in areas like programming. Such a focused approach could lead to more pronounced progress in areas that currently show limited or decreasing advancements.

Within the CA 4 domain, focusing on *Safety*, the analysis conducted as part of this study revealed a 0.25 improvement on an 8-level competence. Despite this limited overall advancement, positive mean progress scores were observed across all sub-competencies. Two of these sub-competencies displayed modest progress, while the remaining two demonstrated only minimal improvements. In the study by Reisoğlu and Çebi (2020), participants did not exhibit growth in their knowledge and skills regarding C4.4 *Protecting the environment*. Nonetheless, progress was noted in the other sub-domains. In the SETCOM intervention, the most limited progress was recorded for C4.2, which pertains to *Protecting Personal Data and Privacy*. Çebi et al. (2022) crafted a training module for pre-service teachers in Turkey, aiming to bolster their digital competencies in technology assimilation, rooted in the DigComp framework. Of the 46-hour curriculum, five hours were specifically allocated to CA 4. This safety module had participants explore online risks and the tactics they adopted to protect themselves. Deductions were drawn about how learners can bolster their safety in online platforms tailored for educational pursuits. Their documented outcomes indicated a circumscribed success in the Safety domain, gauged by a questionnaire grounded in the DigComp framework, as conceptualized by Reisoğlu and Çebi (2020). Considering these findings, we want to highlight that in SETCOM, we had even less time compared to the Turkish programme. Given this constraint, the progress achieved in the CA 4 domain is commendable.

In the domain of CA 5, centred around *Problem-solving*, this study showed a 0.43 average progression among the upcoming teachers. Across the board, all sub-competencies registered positive mean progress scores. Of these, three marked a modest advancement, and the other two showcased medium enhancements. Reisoğlu and Çebi (2020) observed advancements in three sub-competencies. However, they detected no progress in C5.3 *Creatively using digital technologies*, in contrast to the SETCOM intervention, where not only was there medium progress in C5.3, but this sub-competence also stood out with the most significant advancement within the CA 5 domain. We believe that this progression might be attributed to the harmonious integration of Social Emotional Learning (SEL). There is evidence suggesting a potential correlation between creativity and the capacity to recognize emotions (Geher et al., 2017). Additionally, it is worth noting that at the University of Maribor, we are actively striving to embed Problem-Based Learning (PBL) methodologies within our pedagogical practices. This commitment to PBL could also be a contributing factor to the favourable outcomes we witnessed.

Despite observable descriptive variations, the lack of statistically significant differences indicates that the intervention uniformly addressed all DigComp 2.1 areas, promoting holistic competence development. In contrast, the programme devised by Çebi et al. (2022) did not yield improvements across all areas.

Encouragingly, both genders appear to benefit equally from SETCOM intervention across competence areas, aligning with the principle of equity. This is particularly notable given the persistent gender disparity in digital skills. For example, Bratić-Martinović and Banović (2018) found Serbian women lagging behind men in digital proficiencies. Sánchez-Canut et al. (2023) recent literature review emphasized the need for in-depth exploration of women's digital competence. Despite the observed differences in some sub-competencies, it's important to note that the sample consisted of only 12 men compared to 70 women, which could attribute the differences to an imbalance in the sample. Additionally, the small size of the sample could also explain the descriptive values, including the negative ones observed among men. We intend to evaluate the digital gender gap closely after the program finishes.

Our results show a digital gender gap in sub-competencies in CA 2 *Communication and collaboration* (sub-competence C2.2 *Sharing through digital technologies* and C2.1 *Interacting through digital technologies*) favouring females and also male advantage in CA 3 *Digital content creation* (sub-competence C5.3 *Creatively using digital technologies)* and in CA 5 Problem-solving (sub competence C3.1 *Developing digital content).* The observed digital gender gap in our study could be influenced by several factors. Firstly, educational and socialisation patterns may play a role, with women potentially developing stronger communication and collaborative skills due to educational experiences and social norms that emphasise these abilities, thus performing better in corresponding digital competencies. Secondly, men might show greater proficiency in digital content creation and problem-solving, possibly stemming from more interest or exposure in these areas, influenced by cultural norms and educational focus. Lastly, the differential access and usage patterns of technology between men and women could contribute to this disparity. Women may more frequently use technology for communication and collaboration, whereas men might be more inclined towards content creation and problem-solving tasks.

The findings regarding digital literacy are mixed and nuanced. Various studies have shown differing trends: some indicate higher digital literacy among girls, others suggest boys are more digitally literate, and still others find no significant gender-based differences in digital literacy (Peng & Yu, 2022 provide a comprehensive review). A study influenced by the COVID-19 context (Kara, 2021) found that the only notable difference lay in general knowledge proficiency, with male students outperforming their female counterparts, possibly due to males' preference for digital devices. In another study focusing on Hungarian librarians in public libraries, Borbely and Némethi-Takács (2023) employed the DigComp2.1 framework to investigate the influence of gender and age on digital literacy.

Conclusions

Our investigation of the impact of the SETCOM intervention on pre-service teachers' digital competencies, as outlined by the DigComp framework, yielded promising results. The average progress, spanning across various competence areas, reflected the potential benefits of intertwining digital competence enhancement with social-emotional learning.

The SETCOM intervention revealed that both male and female participants developed their digital skills equally, showing that the programme was fair and inclusive. Impressively, the intervention led to considerable progress in areas where some other research, like the one by Reisoğlu and Çebi (2020), observed minimal improvement. This difference highlights how important it is to consider the social and emotional aspects when teaching digital skills.

A significant insight gained from this study is the pronounced efficacy of these interventions, even when implemented within a limited time period. This research not only highlights the effectiveness of the intervention in a short duration but also underscores the immense value of creative and holistic pedagogical strategies. Such approaches are essential in equipping upcoming educators to navigate and thrive in the ever-changing digital world. By focusing on innovative teaching methods and comprehensive curriculum designs, this study contributes to the broader goal of preparing future teachers for the technological challenges and opportunities ahead. Furthermore, we hold a positive outlook that the SETCOM intervention will play a substantial role in addressing and potentially narrowing the digital gender gap. This aspect of the study is particularly crucial, considering the persistent disparities in digital literacy and competence between genders. Our hope is that through targeted and effective interventions like SETCOM, strides can be made towards achieving greater equality in digital proficiency across genders, ultimately contributing to a more balanced and inclusive digital education landscape.

In conclusion, this study underscores the need for more comprehensive research. It highlights the importance of examining various influential factors prior to implementing such intervention programs, including the underlying causes for both the positive outcomes, and especially the negative ones. Understanding these aspects is crucial to optimize the benefits for both educators, specifically higher education teachers in this context, and learners, namely pre-service teachers. While positive trends are encouraging and beneficial, it is equally important to investigate and address any negative trends to ensure effective solutions are developed and applied.

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Educational Transformation: Exploring the Benefits of Generative AI Tools

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Abstract

This article explores the use of generative AI tools in education and describes the results of a case study conducted with students of the Elementary Education Program at the University of Maribor. The study explores the impact of integrating artificial intelligence (AI) into various pedagogical practises, from enhancing traditional classroom activities to supporting academic research and writing. Through practical exercises, students interacted with AI tools such as ChatGPT, Bing AI and Google Bard to enhance academic work, brainstorm thesis ideas and improve educational activities. The study highlights the nuanced role of AI in education, including its potential to personalise learning, support content creation and enhance students' critical thinking and creativity. The focus is on students' need for AI skills in order to use these tools effectively and responsibly. The findings suggest that AI can be a transformative force in education. However, its successful integration requires careful consideration, guided interaction and human oversight to enhance the learning experience without compromising academic integrity.

Keywords: Generative AI, Educational Practices, Critical Thinking, Pedagogical Challenges, Personalized Learning

Introduction

Artificial intelligence (AI) has made remarkable advances in recent years, revolutionising various fields such as healthcare, finance and entertainment. One area where AI has the potential to have a significant impact is also education. Generative AI tools have opened up new opportunities for educators and learners and transformed traditional teaching and learning methods. Generative AI refers to the ability of machines to create or generate content such as text, images or videos that are very similar to content created by humans (LeCun et al., 2015). This groundbreaking technology has the potential to revolutionise the education sector by enhancing the learning experience, promoting personalised instruction, and stimulating student creativity. This paper explores the many benefits and potential drawbacks of using generative AI-intelligent educational tools. By exploring the potential advantages and disadvantages of this technology, we aim to show how it can reshape the educational landscape and empower teachers and learners.

One of the key benefits of using generative AI tools in education is the ability to provide personalised instruction. In traditional classrooms, it is often difficult to cater to the individual needs of each student due to limited resources and time constraints. However, with the integration of generative AI tools, educators can create customised learning experiences that are tailored to each student's individual strengths and weaknesses. This personalised approach can significantly improve student learning outcomes and engagement (Maghsudi et al., 2021).

Furthermore, generative AI tools can be an invaluable aid in content creation and assessment. Educators can use these tools to create high-quality teaching materials, such as quizzes, assignments and learning aids, saving time and effort. In addition, the use of AI in grading and feedback processes can provide prompt and constructive assessments that allow students to understand their progress and areas for improvement. Another notable benefit of generative AI tools is their potential to enhance students' creativity and critical thinking (van den Berg & du Plessis, 2023). By automating routine tasks, students are freed from mundane activities and can focus on higher-order thinking skills. They can explore their creative potential by using AI-powered tools to develop innovative ideas, design projects or even compose music, enhancing their learning experience. However, it is important to recognise the potential challenges and ethical considerations associated with integrating generative AI tools into education. Issues such as data privacy, the bias of algorithms and the need for human oversight need to be carefully considered to ensure responsible and ethical use of this technology (Rodrigues, 2020).

The integration of AI in education is increasingly taking centre stage to improve the quality of teaching and learning experiences. The overview of the articles emphasises the diverse applications of generative AI tools and the various ways in which they can transform the educational landscape.

Generative AI tools such as chatbots and intelligent tutoring systems are at the forefront of this change (Chen et al., 2020; Malik et al., 2018; Chang et al., 2022). These systems are designed to provide a more personalised learning experience by tailoring educational content to students' individual needs, preferences and learning styles. The immediate feedback and tailored recommendations that these tools provide are invaluable in creating an environment that is conducive to individualised learning. Research by Smith et al. (2021), Ong et al. (2019) and Perrotta et al. (2022) extends the application of generative AI to the field of affective computing and suggests that the emotional and social wellbeing of students can be significantly supported by AI tools that are able to understand and respond to learners' affective states. The emotional intelligence of these systems enables a deeper level of interaction where students are exposed to empathetic and personalised responses that could revolutionise support systems in educational institutions. Wu & Yu (2023) and Labadze et al. (2023) provide evidence for the effectiveness of chatbots in higher education and describe their role in streamlining administrative tasks, providing academic support and enhancing learning experiences. The high satisfaction of students interacting with chatbots demonstrates their value as an accessible and practical resource.

Nevertheless, the studies call for continuous improvement of these systems to ensure that they remain relevant to the evolving educational context. The potential of AI to improve learning outcomes is also underpinned by Siemens' (2013) discussion of learning analytics. The use of generative AI to analyse educational data provides a powerful tool for creating adaptive learning experiences that respond to student progress and performance, enabling optimisation of the learning process. Borenstein & Howard (2018) provide important considerations for the careful integration of AI into education. The ethical use of these technologies, particularly in light of privacy and bias concerns, is critical to ensure that their use is in the best interests of students. Koedinger & Corbett (2006) provide an example of the successful application of generative AI by cognitive tutors. These AI-driven systems are tailored to improve learning in various subjects and have shown significant improvements in student outcomes by customising to individual learning pathways. The impact of AI and machine learning in higher education highlighted by Johnson et al. (2015) points to a future where personalised and adaptive learning experiences become the norm, driven by the sophisticated capabilities of generative AI tools. Dillenbourg & Jermann (2007) explored the practical aspects of implementing generative AI scripts to promote collaborative learning and emphasised the role of AI in facilitating group interactions and shared learning experiences.

The discourse on the role of generative AI in education includes its potential and challenges. The ability of generative AI to transform learning experiences depends on the core benefits it offers, such as personalisation of content, allowing students to learn at their own pace and level of understanding (Pratama et al., 2023). Emotional support is another area to which AI can contribute significantly, as it can provide timely and patient help when human resources are limited. Adaptability is also crucial, as AI is able to update and adapt content based on the learner's progress and needs. However, alongside these opportunities, the literature also emphasises the importance of facing up to major challenges. Data privacy is at the forefront, considering the sensitive nature of student data and the ethical considerations surrounding its use (Rodrigues, 2020).

Furthermore, the long-term effectiveness of AI tools in actually improving learning outcomes remains an area for further research. Authors (Ghiațău, 2021; Hinduja & Patchin, 2008; Mokdad & Aljunaidi, 2021; Ma et al., 2008; Sheard et al., 2002) reflect on how technological advances, while beneficial, can also facilitate academic dishonesty. The integrity of academic work is being scrutinised with the advent of AI tools such as ChatGPT and its predecessors. As Pavlik (2023) and Susnjak (2022) noted, the indistinguishability of AI-generated content from human work threatens traditional assessment methods and the nature of academic achievement. The concern is not only about cheating, but also the potential erosion of critical writing and thinking skills that are fundamental to educational development (Susnjak, 2022). It is not just about cheating, but also about what it means: a potential shift in the value system of education from one that encourages intellectual growth to one that prioritises outcomes, regardless of means. Building on the discourse above, exploring the pedagogical implications of generative AI has led us to formulate two research questions.

First, we investigated whether students are able to critically evaluate content taught by generative AI. This research goes beyond simply assessing students' information literacy. It is a barometer of the effectiveness of educational methods in teaching critical analytical skills. The most important question is: Can students navigate AI-generated data with ease and recognise the nuances and biases it contains?

Second, we assessed students' ability to interact effectively with generative AI. Are they able to formulate questions that provide accurate information and convey nuanced understanding? Students' ability to interact with AI can provide insight into their cognitive processing skills and their adaptability to use AI as a tool for deeper learning.

To answer these pressing questions, we conducted a case study with students in the study Programme of Elementary Education. During various exercises, lectures and seminars, these students were confronted with the task of communicating with artificial intelligence. In doing so, they walked a fine line between technology as a pedagogical aid and a potential crutch. Crucially, this case study did not just focus on the negative outcomes, but also looked at bad and good practise. By examining the scenarios where the use of AI did not align with educational goals, we were able to identify missteps to avoid. Conversely, we highlighted successful interactions where AI enhanced understanding, provoked deeper questions and enabled personalised learning pathways. By looking at examples of good and bad practise, the study aimed to provide a balanced view of how AI can be integrated into educational institutions. Such an approach aims to highlight best practise for the use of AI in the classroom and ensure that AI is a strong ally in the educational process, rather than a barrier to genuine understanding and critical thinking.

Methodology

Research design

This study was designed as a investigation of the application of generative artificial intelligence (AI) by students of the Elementary Education Program at the Faculty of Education of the University of Maribor. Observation started in March 2023 in the autumn semester of the academic year 2022/2023 and lasted till november 2023 in the winter semester of the academic year 2023/2024. The integration of generative AI into various pedagogical practises has been observed and analysed. Before the study began, all students involved in the case study underwent a structured lecture on the generative AI tools. These lectures included demonstrations of use and discussions about the capabilities of AI, its application to their specific academic tasks and the ethical considerations associated with its use. This lectures ensured that students were equipped to use AI in their assignments. The selection of ChatGPT, Bing AI and Google Bard as primary tools for this study was based on their availability and ease of use, in addition to their advanced capabilities. ChatGPT was selected due to its ease of accessibility. It only requires a Gmail account to sign up, making it easily accessible to students who are already familiar with Google services. Bing AI was chosen for its integration with the Edge browser, which is a standard component of the Windows operating system used by many students. This integration allows seamless access to the AI tool within a familiar browser environment. Google Bard was selected when it became available on the Slovenian market and offered a new and locally relevant AI resource. The introduction of Google Bard offered students the opportunity to explore and compare different AI platforms, which enriched their learning experience. These criteria — ease of access, integration with commonly used platforms and the opportunity to engage with a newly introduced tool — were key to the decision to use these particular AI tools in the study.

Participants

Students from the third, fourth and fifth year of the Elementary Education Program at the Faculty of Education at the University of Maribor took part in the study, with each group using artificial intelligence (AI) for different academic purposes.

The third-year students, who were 21 years old, used AI to submit and defend their compulsory seminar papers. This cohort included 63 students who integrated AI into their seminar assignments. Fourth-year students, who were 22 years old, used AI to develop ideas for their master's theses, specifically those who chose topics related to natural science and technology. This group consisted of 7 students. Finally, the fifth year students, who were 23 years old, used AI to refine summaries of scientific articles during their lectures. 40 students participated in this activity.

Procedure

The third-year students were tasked with searching within elementary school Science and Technology textbooks for a scientific experiment or a technical product build. Once selected, they had to conduct a science experiment or create the product as if they were teachers guiding a class of pupils, mirroring how teachers would approach such a task. They then used generative AI to suggest improvments to the instructions, content or crafting process. Fourth-year students were observed using generative AI to generate ideas for their master's theses. The role of AI in this process was to find ideas and support their preliminary research. For fifth year students, the focus was on use of generative AI during lectures to improve existing summaries of articles. The AI was used to provide suggestions to improve the clarity and comprehensiveness of the summaries.

Data collection and analysis

The data for this study was collected using a multi-faceted approach to ensure a comprehensive understanding of the impact of AI tools in educational institutions. Primary methods included direct observation and interviews with students about their experiences.

Direct observation: Direct observation during classes and seminars was conducted to gain first-hand experience of how students interacted with the AI tools.

This approach provided valuable insights into the practical application and integration of AI in educational tasks.

Collaborative data review with students: After the initial data collection, the data was first reviewed and analysed in collaboration with the students involved in the study. This participatory approach allowed students to reflect on and articulate their experiences and the impact of AI on their learning and academic work. It also provided students with the opportunity to contribute to the interpretation of the data to ensure that their views were accurately reflected.

Further analysis with faculty members: The data was then further analysed in collaboration with professors from other disciplines within the faculty. This interdisciplinary approach provided a more holistic understanding of the data as it brought in different academic perspectives and expertise. This additional level of analysis helped to contextualise the findings within the broader educational landscape and provide more nuanced insights.

By including student and faculty perspectives in the analysis process, the study aimed to provide a well-rounded picture of the application and impact of AI in education.

Case study

The discourse that follows offers a detailed examination of different scenarios in which generative artificial intelligence has been used in the context of educational tasks. This qualitative investigation explores the nuanced applications of AI and critically assesses its dual ability to both enrich education and, paradoxically, present a potential obstacle to academic integrity and rigour.

At the centre of this investigation is a reflective analysis of student interaction with Google Bard in the process of product improvement, particularly the improvement of a paper-based product. This demonstrates the importance of asking the generative AI the right questions and how a good question can lead to helpful AI suggestions, while a bad question may not be useful. It also illustrates the potential downsides of ill-conceived prompts that can unintentionally encourage over-reliance on technological assistance. In addition, the study explores the use of ChatGPT to provide comprehensive review prompts and constructive recommendations for summaries of scientific articles. This case study compares the benefits of well-formulated prompts that guide the AI to provide substantive feedback with the pitfalls of vague or misguided prompts that do not fully utilise the AI's analytical capabilities. Finally, the discourse is extended to the use of generative AI to generate ideas for master's thesis ideas within the natural sciences. It is shown how a strategically designed prompt can serve as a catalyst for innovative thought processes.

Through these selected examples, the study aims to provide a balanced perspective on the pragmatic integration of generative AI into educational practise. It seeks to illustrate the importance of carefully constructing prompts and deliberately guiding generative AI interactions to ensure that the technology is an ally in cultivating critical enquiry and intellectual autonomy.

Improvements for paper product with Generative AI

In an exercise that combined traditional crafts with modern technology, one student used ai to suggest improvements to a simple paper model — a helicopter as described in a primary school textbook. The textbook contained brief instructions that required simple scissors and a paper insert from the workbook. The student copied the paper insert, cut along the marked lines, folded the resulting strips in opposite directions and attached a paper clip to the narrow end to ensure a graceful descent when released.

Looking to improve on this basic design, the student turned to Google Bard, a generative AI tool, with a prompt focused on enhancing the paper helicopter for use in elementary school. The prompt was simple:

“Provide improvements for a paper helicopter project for first graders in elementary schools.”

“*Here are some suggestions on how to improve the paper helicopter for first graders in elementary schools:*

- *Use stronger paper. Regular writing paper might be too thin to allow the helicopter to hover in the air. Instead, use a more robust paper, like cardstock or scrapbook paper.*
- *Add more support. To make the helicopter hover longer, you could add more support. You can do this by glueing small pieces of paper or cardboard at the bottom of the helicopter.*

- *Design the helicopter to be more aerodynamic. If the helicopter is too heavy on one side, it will quickly tip over. Try to make the helicopter more aerodynamic by giving it smoother lines and reducing weight. (Google, 2023)"*

In this sub-case study, we are presented with a series of missteps that teach us a clear lesson about the importance of understanding the content, question formulation and critical evaluation of generative artificial intelligence proposals. These missteps illustrate a cascading effect where initial misunderstandings and imprecise questioning lead to a fundamentally flawed outcome.

The beginning of the confusion lay in the misidentification of the product. The Slovenian term for 'helicopter' inaccurately described the object, which was supposed to replicate the spinning descent of a maple seed. This initial error in terminology laid the foundation for later misunderstandings. From an educational perspective, this misnomer is more than a simple mistranslation — it represents a disconnect from the underlying scientific concept that the exercise was intended to convey.

Complicating matters further was the wording of the prompt. The student's query to Google Bard was vague and lacked contextual details that are important for a generative AI to provide a relevant answer. It did not specify the age of the students, the pedagogical intent of the project, or the improvement criteria. Effective prompts are the linchpin for the benefit of generative AI — they need to be created with precision and a deep understanding of the context and desired outcome. This is not just a technical requirement, but a fundamental skill in the digital age, where the ability to communicate effectively with AI determines the quality of information that can be extracted.

Finally, the scenario emphasises the critical need to evaluate the response of the AI. Although a generative AI is powerful, it is not infallible. It works on the basis of the input provided and does not have its own judgement. It is therefore the responsibility of the user to critically evaluate the suggestions generated by the AI. In this case, the AI's recommendations were not feasible and conceptually flawed. They suggested improvements that would not improve the functionality of the paper craft as intended.

This triad of errors — misnaming, vague prompts and lack of critical evaluation — forms a teachable moment. It emphasises the need for a comprehensive understanding of the topic, the ability to formulate precise questions tailored to the capabilities of the AI, and the need for a critical mind to critically evaluate the answers. These skills are essential to fully realise the potential of AI in education and avoid the pitfalls that lead to misinformation.

The most common mistakes students make when interacting with generative AI are misnomers and vague prompts. These are not isolated incidents, but a systematic problem that stems from a fundamental misunderstanding of how AI interprets and processes information. Incorrect labelling — due to translation errors, cultural differences or simple misunderstandings — can lead the AI down a path that deviates from the user's intent. At the same time, a vague prompt often leaves too much to the AI's interpretation, which can lead to generic or irrelevant responses.

Because of these problems, students often receive useless or low-quality answers from the AI. For example, if a student refers to the descent of a maple seed as a 'helicopter', the AI will generate advice based on incorrect assumptions about the object's function and design due to the lack of context that humans take for granted. Similarly, when students give a prompt that lacks specificity, such as asking for general improvements without providing context or criteria, the AI is unable to provide targeted, helpful information. This often results in recommendations that are either too broad to be of practical use or that are technically impractical.

Some similar vague prompts discovered in the same sub-case study were:

"Suggest improvements for the implementation of the picture framework in environmental and social studies lesson in the first year of elementary school"

"Suggest improvements for the implementation of origami in environmental and social studies lesson in the first year of elementary school"

"Suggest improvements for the implementation of traffic signs on sticks in environmental and social studies lesson in the first year of elementary school"

These types of prompts almost never provide targeted, helpful information. AI suggest some minor changes to the design that were decorative in nature.

Some better but still vague prompts that were discovered in the same sub-case study were:

"How to improve and critically evaluate the activity for the second year of elementary school, whose instruction is: "We can separate, we can't separate.

Draw: "Given are the following mixtures: water-flour mixture, water-vinegar mixture, water-pumpkin oil mixture, water-rice mixture, water-bean mixture"?"

"Write an improvement for the task below and critically evaluate it. This assignment is for the 2nd grade in elementary school in the subject environmental and social studies. The task requires a jar and a spoon and the following substances: pumpkin seed oil, olive oil, vinegar, rice, salt and flour. The instructions for the task are as follows. Sink. Dissolves. Draw."

One way to improve the prompts would be to ask the generative AI to analyse the prompts and suggest improvements. For example, ChatGPT gave the following answer for the first prompt improvement:

"Your observation about the prompts being too general is valid. Here are some additional aspects to consider for each prompt:

Prompt: "How to improve and critically evaluate the activity for the second year of elementary school, whose instruction is: 'We can separate, we can't separate. Draw': Given are the following mixtures: water-flour mixture, water-vinegar mixture, water-pumpkin oil mixture, water-rice mixture, water-bean mixture"?

1. *Lack of Specific Goals: The prompt doesn't specify what aspects of the activity need improvement. Is it the educational content, the engagement level, or the clarity of instructions?*
2. *Unclear Instruction: The phrase "We can separate, we can't separate. Draw:" is vague. It's unclear whether students are expected to draw the mixtures, the separation process, or something else entirely.*
3. *Evaluation Criteria Missing: There is no mention of how the activity should be critically evaluated. Should it be based on educational outcomes, student engagement, or understanding of the concepts?*

For the prompt, a more effective approach would be to include specific goals for the activity, clearer instructions for the students, and defined criteria for evaluation and improvement. Additionally, linking the activities more explicitly to the learning objectives would make the prompts more coherent and purposeful. (OpenAI, 2023)"

The problem of unclear goals, unclear instructions, and lack of criteria for critical evaluation in student prompts for AI is complex and multifaceted. When students design questions or tasks for the AI, they often face the problem of clearly articulating their expectations or needs. This lack of clarity is due to several factors, including a lack of understanding of how AI works, its limitations, and the best methods for interacting with it. If the goals are not clearly defined, the AI cannot determine exactly what the user expects from it, resulting in inappropriate or incomplete responses. Similarly, if the instructions are unclear or too general, the AI cannot effectively understand and perform the required task. Furthermore, the lack of clear evaluation criteria makes it difficult to assess the effectiveness of AI responses, as without criteria it is not possible to objectively evaluate whether the responses are appropriate or useful. This problem not only reduces the quality of the interaction between students and AI, but also hinders the educational value that AI could have for the educational process.

Students performed slightly better in critically evaluating the AI responses. They recognised that many of the answers were broadly inadequate. This critical thinking ability is a silver lining because it shows that students are engaging with the material and questioning the validity of the information presented. However, the frequency of poor quality responses has a detrimental effect on students' confidence in generative AI. When unsatisfactory interactions repeatedly cloud their experience, scepticism grows. This mistrust can make them reluctant to use AI as a tool for learning and exploration. As a result, they miss out on the potential benefits that AI can offer if it is used appropriately and with a clear understanding of its limitations.

Review prompts and constructive recommendations for academic article abstract

The students on the master's course had the task of jointly creating an optimal prompt to facilitate the review of an abstract of a scientific article. The possibilities of ChatGPT Plus 4.0 were utilised. The aim of the exercise was to demonstrate the importance of creating accurate prompts in order to obtain valuable AI-generated reviews. Students were first introduced to the basics of generative AI and its application in reviewing scientific articles. With an understanding of ChatGPT Plus 4.0's advanced language model trained on a variety of texts, students realised the potential of AI to provide insights that are not immediately apparent to the human eye.

To begin the exercise, they scrutinised the structure and content of typical summaries of existing scientific articles and discussed the key elements that should be present, such as the purpose, methods, results and conclusions of the study.

They also looked at common pitfalls in summary writing, such as over-generalisation, lack of clarity and failure to convey the significance of the research. With this knowledge, the students set out to design a prompt that would not only guide the AI to critically review the summary, but also encourage them to suggest improvements based on specific criteria. The process of creating the prompt involved several iterations, with students discussing and refining the language to maximise clarity and effectiveness. Students randomly selected summaries from international conference proceedings on the Internet.

The final prompt they have developed was as follows:

"The most common way to write abstracts is by using the IMRaD structure, which stands for Introduction, Methods, Results, and Discussion. The abstract title should not be general but must be specific and illustrative, encapsulating the actual content of the summary. The abstract should be at least 50 and no more than 250 words. The questions below assist in writing the abstract structure. Answer them in one to three sentences. The questions are:

- *What is the problem? Present the background. Describe the objective, research questions, and/or hypotheses.*
- *What has been done? Explain your research methods (Type of research you conducted, How you collected and analysed data, Any tools or materials you used in your study, How you mitigated or avoided research biases, and Why you chose these methods.)*
- *What have you discovered? Summarise key findings and conclusions.*
- *What do the findings mean? Summarise the discussion and recommendations.*

Prepare a review considering the above instructions and provide reviewer comments. The article's content, keywords, and title are: "ABSTRACT TEXT"."

When ChatGPT Plus 4.0 was fed this prompt, the AI generated a response that contained a thorough critique of the summary:

"Of course, here are the suggestions for improving the summary:

Title: Change the title to something more specific and informative, for example: "The Impact of Regular Physical Activities on Motivation and Concentration in Elementary School Children".

Introduction and Issues: Clearly define the research question. Add: "The study focuses on how regular physical activities affect the motivation and concentration of children in elementary school."

Methods: Add a description of the research methods used. For example: "We conducted a qualitative study where we interviewed teachers and observed physical activity sessions in three elementary schools. We also analysed the daily routines and schedules of the schools to assess how much time is allocated for physical activities."

Results: Elaborate on the findings by adding quantitative or qualitative data. For instance: "We found that students who participated in daily physical activities showed a 25 % increase in concentration and a 30 % increase in motivation for school work compared to students without such activities."

Discussion: Expand on the section about what the findings mean. Add: "Our research indicates that physical activities benefit students' physical health and significantly impact their academic performance and mental well-being. Schools should seriously consider increasing the time allocated to physical activities."

Keywords: Consider adding or replacing some of the keywords to reflect the content of the abstract more accurately. For example, add "motivation", "concentration", or "elementary school".

I hope these suggestions will help you improve the summary and make it more informative and practical!"

Building on the findings from the first part of the answer, the students faced a new challenge: optimising the process of revising the summary based on the AI's suggestions. While the AI had provided valuable feedback on the summary, the question was how to best utilise these insights to efficiently improve the summary.

Therefore, the students proposed a new approach: They wanted to let the AI do the revision. This would serve as an exercise for advanced prompts and test the AI's ability to apply its suggestions to produce a refined text. With this idea in mind, the students drafted a new, short prompt:

"Write a revised abstract."

This prompt marked a shift from seeking advice to delegating the task of editing, pushing the boundaries of AI's utility in the academic workflow. ChatGPT Plus 4.0 was tasked with integrating its previous recommendations into a coherent and improved summary when given this instruction. The experiment delivered astounding results. Indeed, the AI improved the summary by providing better context and clarity, demonstrating its ability to process and apply feedback constructively.

However, a notable complication arose during the AI's revision. While ChatGPT Plus 4.0 effectively embedded its suggestions into the summary, it inadvertently presented its illustrative examples as factual data. Thus, in its original feedback, the AI suggested supplementing the results with quantitative or qualitative data and provided a hypothetical example: "We found that students who participated in daily physical activities showed a 25 % increase in concentration and a 30 % increase in motivation for school work compared to students without such activities." When revising the summary, the AI inserted this invented example as if it were an actual result of the study.

This incident highlights a critical aspect of the AI's current capabilities and limitations. The AI does not distinguish between hypothetical illustrations and accurate data during input. It processes and spits out information based on the prompts without understanding the underlying truths or falsifications. This poses the risk of spreading false information if the content generated by the AI is not carefully checked.

The sub-case study therefore emphasises an important lesson: the need for careful human oversight when using AI to create or edit academic content. It highlighted that while AI can greatly assist the writing process by suggesting improvements and even drafting revisions, it cannot recognise the integrity of its input and output.

The strategies outlined for mitigating the limitations of AI in academic work are closely intertwined with the integrity of the individual and general ethics in AI. At its core, the relationship between AI and human users is not only about efficiency and accuracy, but also about maintaining ethical standards and personal integrity in the face of increasingly sophisticated technology.

The imperative to use AI as an assistant and not as a substitute for human judgement is closely linked to the concept of personal integrity. Integrity in this context refers to the commitment of individuals – whether they are students, researchers or professionals – to uphold standards of honesty and accuracy in their work. By recognising the limitations of AI and taking responsibility for the end result, they demonstrate their commitment to the truth and ethical standards of their field. This is especially important for academic work, where the authenticity and accuracy of information form the basis for the advancement of knowledge.

Educating students on the effective use of AI also has ethical dimensions. This involves not only technical expertise, but also an understanding of the ethical implications of using AI. For example, relying too heavily on AI for tasks such as writing texts or analysing data can lead to ethical dilemmas such as the unintentional spread of bias, misinformation or plagiarism. By being made aware of these risks, students can make more ethically informed decisions about how and when to use AI in their work.

Emphasising human oversight in the review process is not only a practical measure to ensure accuracy, but also an ethical stance. It recognises that, despite advances in AI, human judgement is irreplaceable, particularly in matters where context, nuance and moral considerations matter. Human oversight ensures that the use of AI is consistent with ethical standards and societal values to prevent the misuse of AI and the erosion of trust in scientific work and technology.

To summarise, strategies to mitigate AI restrictions are not only about improving the effectiveness of AI in academic contexts, but more importantly about preserving the integrity of the individual and ensuring ethical interactions with AI. This approach promotes a responsible use of technology that respects human values and ethical principles, which is essential in an increasingly AI-driven world.

Generation of master's thesis ideas

In the last sub-case study, a student began designing his Master's thesis. The field of elementary school science was chosen and the aim was to bypass traditional survey methods in favour of a practise-based approach. The student intended to develop and explore the educational content of forest trails, an innovative topic that promised both practical engagement and academic research.

After an extensive review of the literature and an evaluation of existing related master's theses, the student developed a prompt that would utilise the generative power of AI to propose unique and innovative activities for the forest trail. The prompt was tailored to the specifics of the study programme and the target audience of ten-year-old children to ensure relevance and applicability. It was as follows:

"I am writing a master's thesis for the elementary education study program. The title of my thesis would be 'Forest Learning Path in 4th and 5th Grade Science Education'. The children are 10 years old. Suggest some ideas that could be implemented and described in my master's thesis. I intend to use unconventional and innovative activities not typically used in schools. The children would be in groups and would have tools to use."

This prompt set the basis for the AI's contribution to creative pedagogical interventions that could be carried out on a forest learning trail. The AI was effectively asked to act as a brainstorming partner and suggest various possible activities to the student, which could be described in detail and evaluated in the thesis.

The AI's response was to suggest several original and feasible activities that matched the student's vision:

"Of course! Here are some suggestions for innovative activities that you could include in a forest learning path for natural science subjects for 4th and 5th-grade students:

1. *Interactive Searches: Each group receives a "forest treasure box" with which they must find various items or organisms. They can examine what they've seen in more detail using magnifying glasses and microscopes.*
2. *"Forest Art": Children collect natural materials (such as leaves, branches, and cones) and use them to create artwork. This helps them understand the different textures and properties of natural materials.*
3. *Listening to Nature: Children are given headphones to listen to different sounds of the forest. They then discuss which animals or elements in nature produce these sounds.*
4. *Interactive Maps: Provide children with interactive maps of the trail, which they can complement with stickers or notes as they discover something new or exciting.*
5. *"Forest Laboratory": Set up a station where children can examine soil, water, or plants with basic laboratory tools such as test tubes, pipettes, or pH strips.*
6. *Digital Explorations: If possible, provide children with tablets or smartphones with apps for identifying plants and animals. With these tools, they can quickly identify and learn about the organisms they find.*

7. *Naturalist's Journal: Children receive a small portable journal in which they record their observations, sketch plants or animals, and write down thoughts about their discoveries.*
8. *Forest Challenges: Set up challenges at specific stops where students must apply different scientific concepts they have learned to solve a problem or puzzle.*
9. *Role of a Scientist: Children can take on the roles of different scientists (botanist, zoologist, ecologist, etc.) and perform tasks typical for these professions.*
10. *Research Projects: Children can choose a topic or organism they are interested in and conduct a short research project. They present their findings to their classmates at the end of the path.*

When planning these activities, it is important to consider safety standards and ensure that all activities are suitable for the age group and the curriculum. Good luck with your master's thesis! (OpenAI, 2023)*"*

Intrigued by the concept of the challenges of the forest, the student has formulated a prompt in the form of a follow-up question to take the matter further:

"Great, I like the idea of Forest Challenges. Could you elaborate on this idea and tell me more?"

The AI responded with an expanded idea and provided a detailed explanation that prompted the student to do further research in the literature.

The AI suggested the following:

"Of course, I'm glad you like the idea of forest challenges. Here is a more detailed description and some examples of challenges that you could use on a forest learning path:

Concept:

Set up challenges at various stations along the forest learning path based on scientific concepts or skills. These challenges are designed to test the children's knowledge, encourage peer-to-peer learning, and stimulate critical thinking. Each challenge should be time-limited and offer points that groups collect. At the end *of the path, groups can see how many points they have accumulated and perhaps even receive a small reward.*

Challenge Examples:

- *Leaf Identification: Groups are given several leaf samples and must determine which leaf belongs to which tree. They can provide one characteristic fact about that tree for an extra point.*
- *“Water Detective”: At a stream or small pond, groups use nets to collect water samples and then identify aquatic animals or plants. For additional points, they can determine whether the water is clean or polluted based on the organisms found.*
- *"Student Becomes Bird": Using binoculars or just their eyes, students observe birds and try to identify at least three different species. For extra points, they can mimic the sounds of these birds or share interesting facts about them.*
- *Wind Direction: Using tools such as windmills or feathers, groups determine the direction of the wind and estimate its speed. For additional points, they can explain how the weather affects forest ecosystems.*
- *“Forest Architect”: Challenge groups to build a shelter or mini dwelling with natural materials in a limited time. This can be linked to learning about animals that make homes in the forest.*
- *“Forest Chef”: Using natural materials (without actual cooking!), groups “prepare a meal” for a specific animal. For example, they could “prepare” a meal for a deer or doe using leaves and cones.*
- *Tracking Observations: Set up artificial animal tracks on the path and have groups figure out which animal passed by. They can describe that animal’s behaviour or what it might be doing in the forest for extra points.*

To successfully implement these challenges, it’s important that all instructions are clear, all materials are available, and the challenges are appropriate for the age group. Additionally, it is crucial to ensure that all challenges are safe and that all environmental guidelines and conservation rules are respected. (OpenAI, 2023)*”*

These detailed suggestions from AI enriched the original concept of the student and showed possible ways to engage young learners in hands-on scientific enquiry. Encouraged by the AI's expanded idea, the student gathered further resources and scholarly articles to support the development of these challenges and ensure they were pedagogically meaningful and implementable.

This sub-case study was a clear demonstration of the practical benefits of AI in an academic setting. The student was able to transform the ideas generated by the AI into a well-rounded dissertation plan that was pedagogically sound and in line with the principles of experiential learning. This experience highlighted the central role of precise prompts in gaining valuable AI input and emphasised that while the AI can act as a catalyst for creative thought, the student controls the actual depth and direction of the research. In addition, the AI recognised the need to pay attention to safety and environmental awareness when carrying out the proposed activities. In order to successfully implement these challenges, all instructions must be clear, all materials must be available and the challenges must be appropriate for the age group. It is also important to ensure that all challenges are safe and that all environmental guidelines and conservation regulations are adhered to. The partnership between the capabilities of AI and the discerning guidance of the human intellect has created a model for the integration of technology into advanced academic research that combines innovation with the solid foundations of educational theory and practise, while ensuring the well-being of participants and the environment.

Discussion

As these selected sub-case studies demonstrate, exploring the application of AI in academia is a representation of its evolving role and the essential partnership between technology and human cognition. The critical examination of these scenarios provides a framework for understanding the nuanced interplay of AI support in academic work.

In the case of improving a paper helicopter design, students were confronted with the challenges of precise language and the importance of context when interacting with AI. This encounter reinforced the imperative of critical thinking when interpreting AI responses, a necessary step to maintain academic integrity and ensure the factual accuracy of course content.

When reviewing and improving a summary of an academic article, the student's interaction with the AI demonstrated the potential of well-articulated prompts to elicit valuable feedback from AI tools. This sub-case study highlighted the ability of AI to act as a catalyst for creative thinking, leading to a deeper dive into the literature to underpin the AI's suggestions. It was a practical demonstration of how AI can contribute to the refinement of academic writing when directed with clear and specific prompts and questions. However, the students encountered a complex problem when using AI for editing. ChatGPT Plus 4.0 actually integrated its initial suggestions into the summary and incorrectly treated hypothetical examples as actual data. This incident highlighted the current limitations of AI in distinguishing between theoretical and actual data and emphasised the importance of critical oversight when using AI-generated material.

In the third sub-case study, in which the student created a plan for a master's thesis centred on learning pathways in the forest, the AI was instrumental in proposing a framework of activities that conformed to the principles of educational and experiential learning. The AI's response incorporated safety and environmental aspects and emphasised its supporting role in the academic process. In this case, the importance of expert human oversight to ensure the relevance, safety and ethical execution of the proposed educational activities was particularly evident.

These sub-case studies demonstrate the delicate balance of using AI as a powerful assistant in academic endeavours. This balance required a nuanced approach to the evaluation of AI performance and its appropriate integration into the research process, which was firmly under the control of the student. The discussions that emerged from these sub-case studies pointed to the need for clear communication with AI and the cultivation of informed scepticism that questions AI outputs while understanding the logic behind its responses.

In synthesising the lessons from these case studies, a blueprint for integrating technology into higher education research and learning emerged. This model encourages innovation while ensuring that the foundations of educational theory and practise are maintained and strengthened. It suggests that, if utilised effectively, AI can become a reliable asset in education, bridging theoretical concepts and practical application to enrich the learning experience and help students navigate the complex landscape of modern education.

The promise of personalised learning through AI, as proposed by Chen et al. (2020), Malik et al. (2018) and Chang et al. (2022), is based on the ability of these systems to tailor educational content to the individual needs of students. However, this personalisation depends on how well students can interact with the AI, particularly in formulating prompts that can elicit the desired educational support. Analysing students' use of generative AI in the classroom shows that students are currently not very adept at using AI. This lack of mastery is a natural barrier to one of the potential risks mentioned in the introduction: the misuse of AI for academic dishonesty. Ghiațău (2021) and Susnjak (2022) have pointed out that the sophistication of AI-generated content could undermine academic integrity. However, given the current level of student knowledge, this threat may be less acute than assumed. Analysis of the use of AI in the classroom has shown that students struggle with the subtleties of prompt engineering, suggesting that while AI can produce high-quality results, the ability to manipulate it for fraudulent purposes is not widespread.

The reference in the introduction to Smith et al. (2021), Ong et al. (2019) and Perrotta et al. (2022) on the role of AI in affective computing also suggests that these tools could also promote students' emotional and social well-being. This aspect becomes particularly relevant when considering the discussion in the introduction about the need for AI systems to provide empathetic and personalised responses. However, the ability of AI to provide emotional support depends on how well students can communicate their needs to the AI. Students' current lack of experience in interacting with AI means that the potential of AI as an emotional support tool has not yet been fully realised.

In terms of adaptability, the introduction claims that AI tools can update and adapt content based on learners' progress and needs. However, this adaptability is only as effective as the ability of users to guide the AI through precise and insightful instructions. Without this ability, the full capacity of AI to adapt to individual learning curves, as demonstrated by cognitive tutors in the work of Koedinger & Corbett (2006), remains unutilised.

It will be necessary to have a curriculum that incorporates AI skills to address these challenges. This would mean teaching students how to interact with AI in a way that is both competent and ethical, and helping them understand the nuances of AI interaction and the importance of maintaining academic integrity. By integrating AI skills into the curriculum, educators could ensure that students are prepared to use AI tools effectively and are aware of the ethical considerations and potential consequences of misuse. This approach would align with the sentiment expressed by Siemens (2013) on the use of learning analytics to create adaptive learning experiences and ensure that the use of AI in education serves the best interest of students, as Borenstein & Howard (2018) and Dillenbourg &

Jermann (2007) emphasise the ethical use of AI and its role in collaborative learning.

In conclusion, this study affirms the transformative potential of AI in education, but calls for a measured approach that emphasises the development of AI skills and ethical guidelines. This would help to mitigate the risks while maximising the benefits of AI by ensuring that the integration of AI into education contributes positively to the learning experience and upholds the values of intellectual growth and academic integrity.

Limitations

While this study is important, it suffers from some crucial limitations. Firstly, its findings are based on a specific sample, which limits its generalisability to a wider population. Experiences and attitudes towards the use of AI in education may vary widely across different educational contexts and communities, but this study may not fully reflect this diversity. Secondly, it was conducted at a single institution, which means that the results may be specific to that setting and not reflect possible differences between universities, their systems and organisational support. In addition, only those who chose to participate were included, which may lead to biassed views. This is all the more true as the 'invisible majority' of students and teachers did not participate, which limits our understanding of their views and experiences. Due to the predominance of women in the teaching profession in Slovenia, there were few men in the sample, which limits the possibility of analysing gender differences. In addition, non-Slovenian-speaking students and educators were not included, which excludes important perspectives.

Future Research Directions

Given the limitations of this study, there are several avenues for further research. It is necessary to extend the investigation to other geographical and institutional areas so that the results can be better generalised. It will also be important to gain a deeper understanding of the views and experiences of the 'invisible majority' in order to gain a more holistic picture of the impact of AI on education. Further research should address the limitations related to self-selection and content validity by improving research instruments and constructs. Including a broader range of students, including those with different linguistic backgrounds and special needs, will be key to achieving greater representativeness. Developing targeted educational programmes that focus on removing misconceptions, highlighting the strengths and weaknesses of AI and promoting open and informed dialogue about the role of AI in education will also be important for future developments and a better understanding of the role of AI in education.

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The Oxymoron of AI in Education

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Abstract

Since the advent of AI systems, mixed reactions have emerged among scientists, educators, and the general public, balancing benefits against drawbacks and concerns. This article explores how teachers in Slovenia, predominantly from Generations X and Y, are adapting to AI in education, contrasting their familiarity with that of their Generation Z students, who frequently engage with AI, especially in social media. Data from 49 primary school teachers and 24 secondary school teachers, gathered via an online questionnaire with 23 questions across four categories (classification, use of ICT, opinions about ICT, and AI in education), reveal their use of ICT and AI in educational settings. Although non-parametric statistical tests indicated no significant differences between primary and secondary school teachers, the findings offer insights into teachers' preparedness for AI integration. Over 70 % have used AI services like ChatGPT, intending to introduce AI to students and incorporate it into tasks. However, less than 30 % feel confident in evaluating AI responses, even though more than half plan to use AI system feedback to enhance their teaching methodologies.

Keywords: teachers, generation gap, AI literacy, digital neo-colonialism

Introduction

In Slovenia, there is a shortage of teachers in some areas, while concomitantly, their bureaucratic burden is increasing, which consumes a lot of time (ironically, despite or precisely because of digitalization) (Anžlovar, 2023; Newman, Mintrom, & O'Neill, 2022). Automation of progress assessments, reports and evaluation could be the solution for the Slovenian public school system. At the same time, an average 16- to 18-year-old girl in Slovenia (Generation Z) uses her smart phone for five to nine hours per day (we are going to see it in a next section) and can create a substantial video on TikTok in less than ten minutes, including music, written text, etc. This fits like a glove into the education system. Nevertheless, the skills of Generation Z can seem like insurmountable tasks to Generations X and Y (Millennials) and an incomprehensible way to spend their free time, which, as we will see below, amounts to several hours a day. Unlike Generations X and Y, for Generation Z (Zoomers), the smartphone is already a personal extension, and generation Z were born before the smartphone saw the light of day, before the iPad came on the market, before Instagram and the word ‘app’ appeared (Finn, 2021; Bruner, 2016; Holwerda, 2011). We can make three statements based on this:

- Generation Z (born 1995– 2009) is not afraid of AI and knows more about using and creating digital content and gadgets than Generation X (born 1965–1980) and Generation Y (born 1981–1994). They are also known as digital integrator, screenagers, iGen (McCrindle, The ABC of XYZ: Understanding the Global Generations, 2018);
- generation Z is digitally literate;
- the Alpha generation (AI generation, screenagers, born 2010–2024), children born shortly before or after the launch of the smartphone and who have grown up in a globalized world, will understand AI systems as something natural and unproblematic.

Is that really the case? And what does this mean for the education system, where screens (also for education) are used every day by children and students, but not necessarily by teachers? How do teachers feel about AI systems? How do they deal with AI systems and how do they understand the system? Are they aware of the generations to which teachers and students belong, and do they adapt the curriculum and methods accordingly?

Many questions, few answers or even more questions arise when we look at Artificial Intelligence and Education (AI&ED: teaching and learning about AI systems; education for AI systems, which aims to develop the ability to understand and to handle AI systems) and in Artificial Intelligence in Education (AIED teaching and learning with AI systems; education with/using AI systems, AI systems for effective teaching and learning) (Holmes, Bialik, & Fadel, Artificial intelligence in education, 2023; Bearman, Ryan, & Ajjawi, 2023; Vincent-Lancrin & Vlies, 2020; Crompton & Burke, 2023).

In the following, we will first, in the introduction, inquire three above mentioned statements; second, we will in chapter 2 present the results of a survey conducted among primary and secondary school teachers, and third, we are going to discuss about results of inquiry and results of a survey.

Assertion 1: Generation gap – Using digital tools and digital technology

Our first assertion is: Generation Z (born 1995–2009) is not afraid of AI systems and knows more about using and creating digital content and tools than Generation X (born 1965–1980) and Y (born 1981–1994), and the reasons for these are as follows. Movies (e.g., Hal in Space Odyssey (2001), Terminator (1984), *Ex Machina (2014), HER (2013), Almost Human (2013–2014), etc.) and predictions by scientists about the power and potential development of AI have shaped Generation Y and especially Generation X. In a study conducted in 2023 (Gartner & Krašna, 2023), Generation Z was asked if they knew movies and TV series in which general AI systems play the main role. They were shown 12 titles, and it emerged that social sciences' students (educational disciplines; age 19–24; N = 254) were largely unaware of them; engineering students (age 19–20; N = 67) were slightly better informed, but only a third of the students knew about a quarter of the films and TV shows presented. Generation Z is therefore unfamiliar with many movies, books and debates that talk about AI as a new dominant species, or even as the destruction of humanity. Nevertheless, elements of what has been shown in films and books already form part of their reality. Therefore, generation Z may not be as afraid of AI systems as older generations, and this could be their reason for using it extensively, or they could be insufficiently mature to see and understand all the potential traps. Perhaps this discomfort of Generations X and Y is because they are talking about things that did not exist at the time they saw these films, and anything unknown arouses suspicion, mistrust, uncertainty and even fear in people (Koetsier, 2023).*

AI systems and a teacher now and in a future

This does not mean that Generations X and Y reject AI systems and do not fully trust them. Across the world (from Canada to Australia (Teachonline.ca, 2018; Chen, Chen, & Lin, 2020), all these systems are already in use; large AI language models (ChatGPT, BingChat etc.) are already creating tasks, questions, and teaching materials; AI systems already recognize spoken words and print spoken words; biometrics (fingerprint, face, and voice) are already used for payment, returning library materials etc.). In addition, some systems are much more successful compared to humans. The Polytechnic University of Valencia for an example has developed a computational tool that attempts to solve these problems. The tool is based on AI and iterative interactions/feedback (Alberola, del Val, Sanchez-Anguix, Palomares, & Dolores, 2016). Eight criteria (e.g., team dynamics, collaboration and organization, satisfaction, etc.) are used to classify students into different teams, and feedback on the success of the teamwork is used to improve the classification. The results show that forming teams in this way is more successful than traditional distribution methods. This is important because part of social and emotional skills is teamwork, which is a desirable skill in the modern companies. With teamwork, we solve complex problems faster and more successfully, we have to be prepared to work with people of diverse characters, with different ways of thinking, which is why we prepare students for teamwork (Team, 2023). Assuming that group work can be understood as teamwork, students divide themselves into groups; we sort them into groups alphabetically, or they draw lots. In the end it can happen that groups are formed randomly and last a whole year or even several years in this formation. This does not strengthen teamwork skills. Another example comes from Canada, where in 2013, 5,540 students wrote the final exam; 100 graders worked for four days, and 28,000 to 32,000 hours were spent: Meanwhile, the machine learning system did it in 10 seconds, and the agreement with the human graders was 97 % to 98 % (Gierl, Latifi, Lai, Boulais, & De Chaplain, 2014). Does this mean that we will no longer need human teachers? Does this mean that we can no longer tell who is scoring except by speed? Does this mean that AI would always pass the Turing Test?

The Turing test, AI systems and a teacher in a future

Alan Turing asked the question in 1950 whether machines can think. The way they were able to show that they could think was with an imitation game in which two people (a human and a computer) answered questions from a third person who did not know which answers were given by the human and which by the machine. Turing says: "I believe that in about fifty years' time it will be possible to programme computers, with a storage capacity of about 10^9, to make them play the imitation game so well that an average interrogator will not have more than 70 percent chance of making the right identification after five minutes of questioning. … I believe that at the end of the century the use of words and general educated opinion will have altered so much that one will be able to speak of machines thinking without expecting to be contradicted." (Oppy & Dowe, 2021)

Can we conclude that in this case we can attribute a certain degree of thinking, intelligence, even mind to the machine? (Sejnowski, 2023; Gonçalves, 2023) Below is an argument that could justify an affirmative answer to the last question:

1. Complex logical processes take place in the brain.
2. Computers carry out complex logical processes.
3. The computer is therefore a brain or has a brain.
4. If you have a brain, you can think.
5. So, a computer can think.
6. If you think, you have a mind.
7. We can conclude from this that the computer has a mind.

Since the first three propositions constitute an inductive argument, the question arises as to whether the reasoning from 1 and 2 to three is strong enough. Before that, the question arises as to how, according to Gozzi, two metaphors, namely “The computer is the brain” and “Thinking is computing”, have become accepted assertions, leading to the conclusion that “A computer has a mind similar to the human mind.” (Gozzi, 1997)

He believes that systems have made enormous progress. The studies shows the great progress of AI in reading since 2016, especially following the advances in NLP (natural language processing) (Khurana, Koli, & Khatter, 2023; OECD, Is Education Losing the Race with Technology?: AI's Progress in Maths and Reading, Educational Research and Innovation, 2023; Min, et al., 2021). The OECD study “Is Education Losing the Race with Technology?” shows no such advances in mathematics. However, the report predicts that AI will eventually be better than the general population in reading and math (OECD, Is Education Losing the Race with Technology?: AI's Progress in Maths and Reading, Educational Research and Innovation, 2023). This means that education will become even more important, as it must prepare people to master the field and acquire the skills to use AI systems and collaborate with AI systems. But how can this be done when young people are more digitally literate than their parents and teachers? And when there is literally a huge gap between the generations. Almost half the children surveyed believe they know more than their parents, and almost as many parents believe they do not know all the traps and tools to protect children from harmful websites, let alone know how to use them (Saliu, Rexhepi, Shatri, & Kamberi, 2022). Whether this already means that young people are digitally literate, we will see below.

Assertion 2: Generation Z is digitally and AI literate

Randomly selected 11 students from two vocational schools, aged 16 and 18, searched their phones for information about how much time they spend on their phones and how much time they spend on social networks per week.

Table 1
Time spent on smart phone between Slovenian teens (age 16 to 18)

No./Age	Use of phone between 11/20/2023 and 11/26/2023	Use of social networks on phone between 11/20/2023 and 11/26/2023	Do you agree or disagree with the claim: I use a smart phone whenever I have time.
S1 – 16	66 h 20 min	46 h	Agree
S2 – 16	45 h 17 min	35 h	Agree
S3 – 16	34 h 45 min	22 h	Agree
S4 – 16	52 h 30 min	29 h	Agree
S5 – 16	38 h 36 min	32 h	Agree
S6 – 16	45 h 35 min	41 h 55 min	Agree
S7 – 18	49 h 34 min	42 h 27 min	Agree
S8 – 18	43 h 30 min	39 h 20 min	Agree
S9 – 18	50 h	41 h 6 min	Agree
S10 – 18	43 h 5 min	25 h 3 min	Agree
S11 – 18	44 h 2 min	37 h 7 min	Agree

On average, they use the phone 6.7 hours per day; more important than this is the average of 5 hours on social networks, which is similar to the UNESCO survey data (Shin, Hwang, Park, Teng, & Dang, 2019) and to the USA where those aged 13–18 year consume on average 7 hours 22 minutes of screen time per day for entertainment purposes (McCrindle & Fell, Understanding Generation Alpha, 2020). The results from countries (Korea, Vietnam) where young people have been using the phone for five years or more are as follows: 60 % use it more than three hours a day, (Vietnam) and 8.3 % (Korea) use it more than 7 hours a day (Shin, Hwang, Park, Teng, & Dang, 2019). They also fully agreed with the claim that they use a smart phone whenever they have time (and also, as they said, when they should not, i.e. during class).

Digital literacy and generation Z

Based on the amount of time students spend on their smartphones, one could conclude that they have digital skills and are digitally literate (Hamadeh, 2022).

However, we should refer to the UNESCO and UNICEF definitions of digital literacy, which are just two among the many definitions:

"*Digital literacy* refers to the knowledge, skills, and attitudes that allow children to flourish and thrive in an increasingly global digital world, being both safe and empowered, in ways that are appropriate to their age and local cultures and contexts." (UNICEF, 2019; Nascimbeni & Vosloo, 2019)

UNESCO: "*Digital Literacy* refers to the ability to seek, critically evaluate and use digital tools (software and hardware) and information (information literacy) effectively to make informed decisions." (Shin, Hwang, Park, Teng, & Dang, 2019, p. 9)

The UNESCO definition sets the bar high, because "Informed decision" means that we have had the opportunity to collect a range of data, to understand it, independently and without control, with the possibility of free choice, to judge, to make a decision and to act in accordance with it. The human being is therefore autonomous and responsible. Based on the above, we cannot attribute digital literacy to most children. The definition also includes the ability to search for and critically evaluate tools. Critical evaluation is a higher cognitive process that we also acquire through education. (Main, 2021) As we have shown in the previous section, according to Koetsier, those working in education (mostly generation X and Y) do not yet have sufficient skills in this respect, even less than learners; the acquisition of knowledge is thus left to the children and young people themselves (Koetsier, 2023). The afore-mentioned UNESCO research (Asia-Pacific) has gathered data to support this assertion: In countries where children have owned smartphones for more than five years, they report that having acquired most of their knowledge themselves and that they have asked their parents and teachers for advice the least often (Shin, Hwang, Park, Teng, & Dang, 2019).

AI literacy and generation Z

We continue with two more concepts, namely digital citizenship, which sets even more conditions and criteria, and AI literacy, which is the loosest definition.

Digital citizenship is defined as "being able to find, access, use and create information effectively; engage with other users and with content in an active, critical, sensitive and ethical manner; and navigate the online and ICT environment safely and responsibly, being aware of one's own rights" (UNESCO, 2017, p. 6).

AI literacy – UNESCO: “Having competencies in both the human and technological dimensions of artificial intelligence, at a level appropriate for the individual (i.e. according to their age and interests)” (Holmes W. , Persson, Chounta, Wasson, & Dimitrova, 2022, p. 5).

The latter definition is the loosest and at the same time the most demanding. It requires many competencies in two dimensions of AI systems (human and technological of AI). According to Vitello and Greatorex, “Competence is the ability to integrate and apply contextually-appropriate knowledge, skills and psychosocial factors (e.g., beliefs, attitudes, values and motivations) to consistently perform successfully within a specified domain” (Vitello & Greatorex, 2022, p. 11). We need to have knowledge about AI systems, about the consequences of using AI systems and about the requirements by products of companies’ (i.e., data transparency).

In the previous section, we noted that young people have more skills in using more digital tools (Koetsier, 2023). But they do not necessary have that much more knowledge about AI tools (Ng T. K., et al., 2022; Yunus, 2021). Firstly, these systems and tools are new (e.g., chatbots, Siri, etc.), and secondly, according to definition of AI literacy, next to AI skills we need critical thinking skills as well as various emotional and social skills (Krug & Noronha, 2023; OECD, The future we want, 2018). We need to have knowledge about it, be ethical and act ethically. We need to ensure a safe environment, be caring, collaborative and responsible (European Parliament, 2023).

Assertion 3: The Alpha generation will understand AI systems as something natural and unproblematic.

The fact that generation Alpha (AI generation, screenagers, born 2010–2024), children born shortly before or after the smartphone appeared on the market and who have grown up in a globalized world, will understands smartphones and smart devices as part of their everyday life is natural, as they are surrounded by these devices, and their environment (e.g., parents, siblings, guests in restaurants, stores, hospitals, fast food places, etc.) uses them all the time (McCrindle & Fell, Understanding Generation Alpha, 2020). With Generation Alpha, it’s a matter of observation: they observe what is happening in society, they imitate it and consequently, they also live it (National Research Council (U.S.). Committee on the Science of Children Birth to Age 8: Deepening and Broadening the Foundation for Success, 2015). They learn in diverse ways and values incorporating digital devices into learning environment (Zamarripa, 2023). Therefore, whether they see AI systems as something unproblematic or not, whether they are AI competent and whether they will still be able to doubt, to think and to be autonomous people, is partly the burden of the three generations that precede them.

In education, all three generations not only need to acquire AI skills and AI competencies to be up-to-date, modern and advanced, but must also bear in mind that digitalization and AI technology received a major boost during the COVID-19 pandemic (WHO: Europe, 2023), when they became popular with the appearance of the Open AI Chat GPT. The pandemic went global, as well as digitalisation and AI systems as their consequences, and similar to what happened in the USA after September 11, 2001, in the name of threat and safety, we renounced our individual rights and principles, one's right to privacy and personal autonomy (Hertel & Buerger, 2023; Lyons, Davis, & Kjaerum, 2021). Given the short period of use of AI systems, no in-depth studies have yet been carried out that take into account the various short and long-term influences and the consequences (and not just the improvement in student grades for all those involved in education) (Bearman, Ryan, & Ajjawi, 2023).

Our aim of the study was to research if there are significant differences between different groups of teachers (comparing primary and secondary school teachers) in the use of ICT and AI systems in educational activities or if we can attribute the results to a single Generation X and Generation Y, and thus confirming the reasoning behind the three assertions we made in the introduction.

We have known too little to decide to use hypothesis and we rather check the following research questions where we want to see if there are differences between primary and secondary school in:

- What are teachers' opinions and use the ICT equipment?
- What are teachers' opinions about their students' abilities to evaluate the data?
- What are teachers' opinions about AI and use the AI in the education?

Method

From the introduction we explain that we did not use hypotheses but we rather focus to the research questions. In these questions we wanted to see if there are significant differences between different groups of teachers.

During September and November 2023 (start of the new school year in Slovenia), we asked teachers from primary and secondary schools to answer an online questionnaire about using ICT and AI systems in educational activities. We prepared 23 questions, three of which were conditional (dependent on answers in previous questions). Questions were prepared for this research and are grouped into 4 categories:

1st category of questions were classification questions and consist of 4 questions.

2nd category of questions consists of 4 question and was aimed to get the feedback about the use of ICT equipment.

3rd category of questions consist of 2 questions was aimed to the opinion about the use of ICT in the education

4th category of questions of questions consists of 9 questions (+2 conditional questions) and were about the AI in the education.

Years of experience have taught us that the return rate for research in the last decade is generally low; therefore, obtaining 75 valid responses is considered a substantial sample size. Our sample includes 49 primary school teachers and 26 secondary school teachers. The average years of experience are similar for both groups: 18.8 years for primary school teachers and 19.1 years for secondary school teachers. However, the standard deviations differ slightly, being 9.9 for primary school teachers and 12.2 for secondary school teachers.

We present the sample using descriptive statistics. Based on the data collected, we also prepare inferential statistics. The majority of our data were collected through closed-ended questions (which will be detailed in the results section). Additionally, some questions allowed for multiple answers. Given the nature of the data, we employed non-parametric tests, such as the Chi-square test and the Mann-Whitney or Kruskal-Wallis tests.

Presentation of the sample

In this topic we present the sample. We compare primary and secondary school teachers in different aspects which seems interesting for this topic. We therefore did not present all the results we got from the questionnaire because it was not important for this article.

The presentation of the sample is by the age of the teachers based on the school they teach in (Table 2).

Results

We will present the findings from our collected data in this topic. As previously mentioned, we will showcase the sample and some interesting findings that are relevant to this article. However, we will not present all the data since they do not provide any new insights into the scope of this article.

Table 2
Teachers' years of employment

School	Average number of years of employment.	Standard deviation
primary	18.8	9.9
secondary	19.1	12.2

One of the classification questions was how teachers use their smart phones. Respondents could choose between 4 possible answers (see Table 3).

Using digital tools and digital technology

Table 3
Smartphone use (One answer possible)

School	Primary	Secondary
I don't have a smartphone.	2 %	4 %
I use a smartphone several times a day.	49 %	58 %
I use a smartphone each hour.	41 %	29 %
I use a smartphone whenever I have time.	8 %	8 %
Total	100 %	100 %

Despite the differences (i.e., primary school teachers use smartphones more often (almost 41 %, each hour) than secondary school teachers (29 %, each hour), we have established that there is no significant difference between primary and secondary school teachers in their use of the smartphone. (χ^2 = 1.13; p = 0,769)

During the COVID-19 pandemic, most teachers worked from home, and for some it was necessary to use haptic devices (e.g., a tablet computer with an interactive pen). Therefore, we asked them how they use tablets in their life.

Table 4
Use of tablet (One answer possible)

	Primary	Secondary
I don’t use it.	33 %	29 %
I used it during distance education, but not anymore.	0 %	0 %
Rarely (a few times a year).	20 %	17 %
Occasionally (a few times a month).	29 %	21 %
Often (a few times a week).	12 %	21 %
Every day.	6 %	13 %
Total	100 %	100 %

Most teachers do not use tablets (Table 4) but if they do use it, it is only few times a month. Tablets were most useful during the remote learning as a haptic device where teachers could use them as blackboard. This use of tablet is not suitable for every teacher though. No statistical difference is observed between teachers from primary and secondary schools ($\chi 2$ = 2.07; p = 0,723).

Table 5
Use of computer (One answer possible)

	Primary	Secondary
Only at work.	0 %	0 %
At work and occasionally at home (a few times a month).	8 %	13 %
At work and often at home (several times a week).	24 %	29 %
At work and every day at home.	67 %	58 %
Total	100 %	100 %

Results show that most teachers use computer every day. We know that some data manipulation can only be made in the computer. The same could not be achieved with the phone or tablets. We expect the result but we do not like the fact that some teachers use them only occasionally at home. Teaching is a living profession and need to be constantly monitored and evolved. No statistically significant differences between primary and secondary school teachers are confirmed ($\chi^2 = 0.64$; $p = 0{,}725$)

For the formal education about ICT, we have multiple answer question where teachers could pick answers from 4 options.

Table 6
Formal education about ICT

	re-sponds
Yes, as part of the study,	40 %
Yes, on-the-job training,	81 %
Yes, training to career improvement,	44 %
No, the offered professional development courses would not bring me new knowledge.	0 %

We anticipate that most of the teachers have on-the-job training and this proved correct (81 %). One interesting aspect of the sample is that around 40 % of teachers do have ICT courses during their study programs to become teachers (39 % for primary school teachers and 41 % for secondary school teachers). Training for the career improvement was picked by 44 % of the teachers. Yet none of the teachers feel so competent in ICT that they would not need additional education in ICT.

Opinions about ICT

Whether we over-emphasize ICT in education was a question posed to see what teachers thought about ICT in general. We intentionally include the question in the negative form with the aim to establish whether teachers were answering the question automatically or if they were reading the question carefully.

Table 7
Do you think we put too much effort into ICT in education? (One answer possible)

	Primary	Secondary
Do not agree at all.	18 %	17 %
Disagree	51 %	35 %
Undecided	16 %	30 %
Agree	12 %	13 %
Strongly agree.	2 %	4 %
Total	100 %	100 %

We can see differences in opinion between primary and secondary school teachers (Table 7), but we could not prove a statically significant difference between the groups ($\chi^2 = 2.71$; p = 0,607). Interestingly, primary school teachers are more inclined to apply ICT in education than are secondary-school teachers. Almost 70 % of primary school teachers do not agree with the statement that we put too much effort into the application of ICT in education, while 52 % of the secondary teachers share this opinion.

Another provocative question we asked the teachers was whether they use ICT incorrectly. The results here are even more interesting than in the previous question.

Table 8
I use ICT incorrectly. (One answer possible)

	Primary	Secondary
Do not agree at all.	0 %	13 %
Disagree	43 %	30 %
Undecided	37 %	43 %
Agree	18 %	9 %
Strongly agree.	2 %	4 %
Total	100 %	100 %

At first sight, the data seem to indicate that teachers from primary and secondary schools have different opinions, but the statistical analysis does not prove this. The χ^2 likely hood ratio shows a possible tendency ($\chi^2 = 8{,}45$; $p = 0{,}061$). But the Mann-Whitney ($U = 509.00$; $p = 0.483$) test show that there is no significant difference between the two groups of teachers.

For our research, another question about the opinion of the teachers was interesting. We asked the teachers if they thought their students knew the quality and validity of information gathered on the internet.

Opinions about AI systems

Table 9
Do you agree that your students know the quality and validity of information gathered on the internet? (One answer possible)

	Primary	Secondary
Do not agree at all.	12 %	9 %
Disagree	53 %	43 %
Undecided	27 %	22 %
Agree	4 %	26 %
Strongly agree.	4 %	0 %
Total	100 %	100 %

Primary school teachers feel that they have less competent students than secondary teachers, but there is no significant difference between teachers' opinions ($\chi^2 = 8{,}37$; $p = 0{,}079$) despite the fact that the tendency could be observed.

We asked the teachers if they are capable of distinguishing between text written by a human or that generated by an AI system.

Table 10
Do you think you can distinguish which texts were prepared by a human and which by an AI system? (One answer possible)

	Primary	Secondary
I am often surprised that I cannot differentiate between these texts.	39 %	25 %
I consider myself about halfway successful.	33 %	54 %
I recognize many of them, but I have problems with some of them.	24 %	21 %
I almost always recognize it, very rarely have problems.	4 %	0 %
Total	100 %	100 %

The data (Table 10) show that almost 39 % of primary school teachers have a real problem recognizing the authors of a text, while 25 % of secondary school teachers report the same. A 50 % success rate in distinguishing between texts is claimed by 33 % of primary school teachers and 54 % of secondary school teachers. Despite the obvious difference, there are no significant differences between primary and secondary teachers ($\chi^2 = 3.48$; $p = 0.279$).

Table 11
Do you follow what is happening in the field of artificial intelligence? (One answer possible)

Opinion of the teacher.	Primary	Secondary
In principle, I'm not interested (I don't have time).	4 %	4 %
I heard and will look.	12 %	12 %
I looked and I'm not impressed.	2 %	4 %
I looked and I have a bad feeling.	12 %	12 %
I looked it up and I think it's great.	16 %	8 %
I looked; I think I will have to adjust my work.	22 %	33 %
I will use or I use it in my work.	31 %	2 %
Total	100 %	100 %

We can see slight differences between primary and secondary teachers, although even here there is no statistical difference between the groups ($\chi^2 = 1.93$; $p = 0.926$). Secondary teachers are slightly more interested in the use of AI systems than their colleagues from primary schools.

The use of AI systems

We sought to establish which AI applications teachers knew and whether they used it. Therefore, we prepared a question in the survey where we asked them to select all the AI applications which they know. They could choose between well-known applications (Chat GPT, Bing Chat, Skype, AI to generate images, Office 365) or choose “I haven’t tried it yet”.

Table 12
What AI systems have you tried using? (Have you registered to use them)? (Multiple answers are possible.)

	Primary	Secondary
Chat GPT	82 %	75 %
Bing Chat	31 %	29 %
Skype	1 %	25 %
AI to generate images	35 %	29 %
Office 365*	**78** %	**54** %
I haven’t tried it yet.	6 %	1z %

** In this category we discover significant difference between teachers*

As expected, most teachers know Chat GPT. But we did not expect that many more secondary teachers did not use AI systems; perhaps they do not know that they are using AI. Moreover, we did not expect that such a small number of teachers would know Bing Chat.

A statistically significant difference between teachers was found in the area of Office 365. The χ^2 test shows statistically significant differences between groups ($\chi^2 = 4.18$; $p = 0.041$). The same was confirmed with the Kruskal-Wallis test ($H = 4.13$; $p = 0.042$) and proved that there is significant difference in Office 365 category.

Encouraging results show that less than 10 % of primary school teachers (6.1 %) have not tried the AI tools, but the results are less encouraging for secondary school teachers (16.7 %). Though this seems a significant difference between groups, this is not the case ($\chi^2 = 2.07$; $p = 0.151$).

Application of AI systems in education

The AI is here to stay. It is the teachers' job to apply it to the best for the educational outcomes. We present the findings in this section of the article.

Table 13
How do you think learners use artificial intelligence systems?
(Multiple answers possible)

	Primary	Secondary
For writing (homework) assignments.	71 %	75 %
As a point of interest.	48 %	37 %
To find ideas.	60 %	58 %
To find additional resources.	35 %	33 %
To explain learning content.	42 %	42 %
To translate between languages. *	**58 %**	**79 %**
For fun.	60 %	67 %

** In this category we observe tendency*

From the data we can see a difference in the topic "To translate between languages". The χ^2 test ($\chi^2 = 3.06$; $p = 0.066$) does not confirm the difference between the groups but the tendency could be observer. Even more subtle test, the Kruskal-Wallis test ($H = 3.02$; $p = 0.082$), does not prove statistically significant differences between groups but we could observe tendency here.

Table 14
Are you planning to use artificial intelligence systems in classroom?

	Primary	Secondary
No, I achieve all learning objectives without using AI systems.	4 %	4 %
I am not sure.	4 %	4 %
I need some more time.	35 %	46 %
I will use it this school year for some content.	31 %	17 %
I will definitely use it again on the appropriate occasions.	25 %	29 %
Total	100 %	100 %

At first sight, there seem to be differences between the groups of teachers, but ($\chi^2 = 1.84$; $p = 0.765$) confirms no difference between groups.

Table 15
How do you plan to use artificial intelligence systems? (Multiple answers possible)

	Primary	Secondary
I will introduce students to the use of artificial intelligence systems. [1]	70 %	73 %
I will give the students a task to use an artificial intelligence system. [2]	67 %	82 %
We will evaluate the products (texts, images) prepared by the artificial intelligence system. [3]	22 %	27 %
We will use the products of artificial intelligence systems as building blocks in our work. [4]	56 %	54 %

[1]($\chi^2 = 0.02$; $p = 0.884$) [2]($\chi^2 = 0.87$; $p = 0.350$) [3]($\chi^2 = 0.11$; $p = 0.740$) [4]($\chi^2 = 0.00$; $p = 0.955$)

There is no significant difference between groups of teachers in the question about how teachers are planning to use AI systems .

Teachers will introduce AI systems (70 % in primary schools and 73 % in secondary schools), therefore more than 2/3 will give students tasks and half of these teachers plan to use AI as a building block.

Importance of understanding the inner working of AI systems

There are vast unknown about the AI inner system workings among the people. Most of the time these processes are not understandable to the non-engineering persons who do not engage into the AI developments. Sometimes the AI neural network weights cannot be explained even by the designers of AI systems (Maclure, 2021; Zhang, Zhou, & Saab, 2023). But we do know that AI system needs data and algorithms to function. The teachers' opinion in these two topics is presented in this section.

Table 16
We need to know what data were used for training the AI system.

	Primary	Secondary
It doesn't matter at all.	0 %	0 %
In principle it does not matter.	9 %	0 %
It is important.	27 %	42 %
It is very important.	58 %	54 %
I have no opinion.	7 %	4 %
Total	100 %	100 %

Data transparency is (very) important for teachers: almost 85 % of primary school teachers and 96 % of secondary school teachers think that it is very important to know what data UI systems used to learn. Not only this, but according to the next table, knowledge about algorithms is also important although less so than data transparency. The insight is important for us despite the fact that there are no statistically significant differences between primary and secondary school teachers in this opinion ($\chi^2 = 3.44$; $p = 0.328$)

Table 17
Importance for Teachers to Understand Algorithms Used in AI Systems for Logical Reasoning.

	Primary	Secondary
It doesn't matter at all.	2 %	4 %
In principle it does not matter.	22 %	13 %
It is important.	40 %	33 %
It is very important.	27 %	38 %
I have no opinion.	9 %	12 %
Total	100 %	100 %

The data indicate the significance teachers place on understanding the algorithms AI systems use for logical reasoning. When combining the responses for 'It is important' and 'It is very important', we observe that approximately 67 % of primary school teachers and 71 % of secondary school teachers believe it is crucial to comprehend the underlying principles of AI algorithms. However, there is no statistically significant difference in opinions between the two groups of teachers on this matter ($\chi^2 = 1.98$; $p = 0.740$).

Discussion

At the beginning of this section, we made three statements. We will challenge them and combine with the results presented above. Namely, members of our research group belong to Generation X (41 %) or to Generation Y (34 %) (we imply the results from the years of employments and the statistical age when they graduate => 3/4 of them). The rest of teachers are post-Y generation (9 %) and pre-X generation (16 %). Secondary school teachers work with students that belong to generation Z and primary school teachers work with students that belong to a first half of the Alpha generation. So, we wanted to know if there are significant differences between primary school teachers and secondary school teachers in the attitude towards and in the use of ICT and AI in the education.

Using digital tools and digital technology

According to our data in the introduction where students (generation Z), named how much time they spend on social networks per week, and that they fully agreed with the claim that they use a smart phone whenever they have time, compared to other studies (Chan & Lee, 2023; YPulse, 2023; McCrindle & Fell, Understanding Generation Alpha, 2020; Shin, Hwang, Park, Teng, & Dang, 2019; Koetsier, 2023) and to data from our main study about teachers using a smartphone, there is a generation gap. Less than 10 % would use a smartphone whenever they have time. But around 1/3 of teachers use tablets, and more than half, almost up to 2/3, of teachers use a computer every day.

According to the results of our study, formal education about ICT has been available to 40 % of teachers during their study and most of the teachers have on-the-job training and this proved correct (81 %), so this maybe a reason why they more often use a computer instead of a smart phone. Only one-quarter of primary and secondary school teachers from our research thinks that we put too much effort into ICT in education (Table 7). They are also interested in use of AI systems, although there is slight difference between primary and secondary teachers: secondary teachers are slightly more interested in the use of AI systems than their colleagues from primary school but we could not prove a statically significant difference between the groups. This is interesting comparing with results about plans to use artificial intelligence systems in classroom. Almost half (46 %) of the secondary school teachers claimed that they would need some more time, but one third (29 %) will definitely use it again on the appropriate occasions. The researches about teachers need to adopt AI in the education is evident in other countries too (Ottenbreit-Leftwich, et al., 2023; Sun, Ma, Zeng, & Jin, 2022).

ICT and AI in education constitute reality: they are already here. So, it is quite discouraging to see that still 1/4 of teachers think we put too much effort into ICT and that 1/3 of secondary school teachers are undecided. A similar profile pertains to monitoring the development of AI in education: 1/3 is not interested, not impressed, or has a bad feeling, and 2/3 of teachers think that it is great, that they will have to adjust their work and will use it or are using it in their work. Also, encouraging results show that less than 10 % of primary school teachers (6 %) have not tried the AI tools, but the result is less encouraging for secondary school teachers (17 %). Therefore, this does not mean that Generations X and Y reject AI systems and do not fully trust them, they are just more cautious as we could also see in other studies (Chan & Lee, 2023).

Opinions about AI systems

When they are reading about the abilities and possibilities of AI systems, a good third of teachers (Generation X and Y) describe their emotions as discomfort and fear, a quarter of them feels anxiety. 12 % of both, primary and secondary school teachers are having bad feeling considering AI systems. Generation Z on the other hand doesn't feel like this and is, in contrast to Generation X and Y, unfamiliar with many movies, books and debates that talk about AI as a new dominant species, or even as the destruction of humanity. Nevertheless, elements of what has been shown in films and books already form part of their reality.

As we could see in introduction, all these systems are already in use across the world – from Canada to Australia (Teachonline.ca, 2018). In addition, some systems are much more successful compared to humans. According to our research, almost 39 % of primary school teachers have a real problem distinguishing human authors of a text from AI generators, and the same goes for 25 % of secondary school teachers. There is a success rate of about 50 % for distinguishing between human and AI texts for 1/3 of primary school teachers and more than half (54 %) of secondary school teachers. Moreover, not even one secondary school teacher (and 4.1 % of primary school teachers) thinks that she almost always recognizes who wrote a text. Despite the obvious difference, there are no significant differences between primary and secondary teachers. Difficulties in recognising the difference between a human text and an AI text are evident in other researches (Ottenbreit-Leftwich, et al., 2023; Dalalah & Dalalah, 2023; Köbis & Mossink, 2021).

In the light of the results of the survey discussed so far, we can affirm first assertion: *generation Z (born 1995–2009) is not afraid of AI systems and knows more about using and creating digital content and tools than Generation X (born 1965–1980) and Y (born 1981–1994*). Between last two there is no statistically significant differences.

Application of AI systems in education and importance of understanding the inner working of AI systems

The AI is here to stay. It is the teachers' job to apply it to the best for the educational outcomes. If we connect the latter with the results from, how do you think the students are using the AI systems, results are interesting. Namely, among primary school teachers, 71 % and 75 % among secondary school teachers think that students are using AI systems for writing homework assignments. Whether this already means that young people are digitally literate, we will see below. We could generalise that at this moment, teachers in Slovenia should not give students written homework assignments if they are not going to defend it and critically evaluate it. This implication is obviously not favourable for teachers because the use of AI in education could undermine learning activities. Teachers need additional training and a transfer of good practice as other studies also proved (Baidoo-Anu & Owusu Ansah, 2023). “In view of this, teachers need to learn not only how to use technology but also how to successfully integrate it into their curricula.” (Kim & Kim, 2022, p. 2).

More than 1/3 (35 %) of primary school teachers and a little less than half (46 %) of secondary school teachers think that they need more time to use AI systems in education to work with learners, and approximately half of them intend to use it. Half the teachers could be a good number, but when we asked them how they were going to use it, the results were no longer so promising. They aim to provide an introduction (71 % to 73 %), give assignments to use AI systems in education (67 % primary school teachers and 82 % secondary school teachers) and they will evaluate the products (texts, images) prepared by the artificial intelligence system (22 % to 27 %). If we take into account the data (i.e., Do you think your students know the quality and validity of the information gathered on the internet?) where teachers are convinced that their students are incapable of assessing the quality of information gathered on the internet (more than half of primary school teachers), then how do they consider that students would know the validity of the information received from AI systems? We guess that this is still unknown for them. Therefore, they do not know how to solve this task, and they postpone it for later. But it is encouraging that most of them are not avoiding the problem, and they will face the challenge of AI systems and do what they can to use them (Kim & Kim, 2022). Teachers will have to »help the next generation face the reality of the world and develop instruments and ways of navigating this reality with integrity. Engage with generative AI tools with your students in person, when possible. « (Ross, 2023). The development of digital competencies among teachers is important as their lack can hinder students’ digital competence development (Redecker C. , 2017).

According to UNESCO and UNICEF, digital literacy, digital citizenship, and AI literacy are essential competencies in today’s world. These competencies require not only the ability to search for and critically evaluate digital tools but also a deep understanding of AI systems. This includes knowledge about the consequences of using AI systems and the requirements for data transparency in company products.

Study reveals that a significant majority of primary (85 %) and secondary (96 %) school teachers believe it is crucial to know what data an AI system uses in its learning process. Furthermore, while knowledge about algorithms is also important, data transparency is prioritized.

This insight remains relevant despite the lack of statistically significant differences between the opinions of primary and secondary school teachers. However, achieving this level of understanding is challenging. The inner workings of AI are often not apparent to general users, and a deep understanding is typically limited to the system's design engineers (Olah, 2018; Xiang, 2022; BBC, 2018). This gap in understanding underscores the need for educational efforts to demystify AI technology for educators and students alike.

The use of AI systems

The third point discussed in the initial section of this article focuses on the alpha generation, also known as the AI generation or screenagers, born between 2010 and 2024. These children, who arrived into the world around the same time as smartphones, have been raised in a highly globalized environment. As a result, they are likely to perceive AI systems as a natural and unproblematic part of their lives. This perspective stems from their constant exposure to these technologies. They grow up seeing not only their family members – parents and siblings – but also people in various public spaces like restaurants, stores, hospitals, and fast-food outlets, regularly using these devices.

If we just take into the consideration the report from the Council of Europe, which states the following "many governments around the world have purchased and widely deployed proprietary and commercial AI systems without sufficient understanding of what the systems do, what they achieve, how they affect learners and teachers, and so on" (Holmes W. , Persson, Chounta, Wasson, & Dimitrova, 2022, p. 44); these companies are without accreditation and without being directly accountable to learners (Holmes W. , Persson, Chounta, Wasson, & Dimitrova, 2022; Bhuiyan, 2023). Also, as already established, few teachers have the knowledge or skills to properly evaluate claims made by private companies about AI systems or have the digital literacy skills needed to understand what its data suggests. During the pandemic, the public education system in Slovenia started using MS Teams, mandatory cameras (without filters at that time), as well as

Zoom and many other applications and tools. We sought to establish which AI applications teachers knew and whether they have tried using it. Given our everyday use of multinational products, e.g. Google (Alphabet Inc.): Search, YouTube, Translate, Scholar; Microsoft (365), Netflix, and Tiktok for educational purposes, a statistically significant difference between teachers was found in the area of Office 365 where 78 % of primary school teachers agreed compared to secondary school teachers (54 %).

With this in our mind and now the use of their chatbots, we can ask ourselves who shapes education, who has a monopoly on education? Is it the government or private individuals and companies who come from a certain environment, with an objective that is never altruistic in the private sector, but always with the aim of increasing this or that power? Among teachers, 96 % use Google, 85 % YouTube, 62 % Facebook, 51 % Booking, and 44 % Pinterest. On the other hand, only 10 to 15 % of teachers are using the social media apps that are mostly used by generation Z (Tiktok and Snapchat), and this is another generation gap. We must know that these companies (with different social media apps) with their data and information promote specific ideologies and a certain lifestyle, a certain language, establish stereotypes, and limit alternatives and choices, while also limiting the diversity of the world, creativity and openness of mind. Ultimately, this means global mind control. As they write in the report, we can speak of digital colonialism (sometimes called digital imperialism and digital neo-colonialism). This implies a brave new world, but not necessarily for every state, for every government, but for some of them and for some multinationals companies and some individuals. Alpha Generation can also be said as the generation that understands technology most and doesn't know the world without social networking" (Arifah et al., 2021, p. 139) Therefore, for Alpha generation AI systems are natural thing, whether they see AI systems as something unproblematic or not, whether they are AI competent and whether they will still be able to doubt, to think and to be autonomous people, is partly the burden of the three generations that precede them.

Conclusion

The exploration of AI systems in education, particularly in Slovenian primary and secondary schools, reveals a complex landscape without significant differences between primary school teachers and secondary school teachers. Despite the discomfort and fear expressed by a significant portion of primary and secondary school teachers (Generations X (born 1965–1980) and Y (born 1981–1994)) towards AI systems and lack the necessary knowledge and skills to effectively utilize this technology, there is a recognition of its inevitability in education. The challenge lies in equipping teachers with the necessary knowledge and skills to effectively utilize AI in their teaching. This is especially crucial given that Generation Z (born 1995–2009) is spending significant time on smartphones and social networks; moreover, with young people often being more skilled at using AI tools than their parents and teachers, it follows that Generation Z's digital skills do not necessarily translate into digital literacy as defined by UNESCO and UNICEF.

The study reveals a generational gap between generations X, Y and Z, with teachers less likely to use smartphones but more likely to use computers and tablets. While teachers recognize the need for AI in education, they express concerns about their ability to use it effectively. The study concludes that there is a need for improved AI literacy among both students and teachers. This presents an opportunity for intergenerational learning and collaboration in the educational use of AI systems.

In the article we address the rapid digitalization and proliferation of AI systems during the COVID-19 pandemic, which has led to widespread use of these technologies in education. However, it raises concerns about the lack of understanding and scrutiny of these systems, particularly those developed by private companies. While these technologies offer numerous benefits, there is a need for careful consideration of their potential impacts on education and the potential for digital neo-colonialism, which has been expanding in recent years and it cannot be overlooked. While the Alpha generation (born 2010–2024) is likely to be comfortable with AI systems, and AI systems will become more integrated into education, it is crucial to ensure that these technologies are used in a way that promotes equity and inclusivity.

Based on the findings reported in the manuscript future lines of research should be to see if there are significant differences between teachers (Generations X and Y) and students (Generation Z and Alpha generation). In conclusion, while AI presents numerous opportunities for enhancing education, careful consideration must be given to its implementation. Bridging the generational gap in AI literacy, promoting intergenerational collaboration, and guarding against digital neo-colonialism are key to ensuring that AI systems serves as a tool for empowerment rather than exclusion in the educational landscape.

Ask Siri: “What is the meaning of life?” In 2019 she answered: “I don’t know, but I think there’s an app for that.” And “I can’t answer that now but give me some time to write a very long play in which nothing happens”. (Weber, 2019, p. 46)

Following major developments in the field of AI and in computer science, Siri in 2023 gave us the following answers: “We are just a speck in the vastness of time and space. But don’t let that dishearten you. It takes every single part of us to make the beautiful mosaic that is our universe.” And “Some say it’s about appreciating the little thing. So, I guess that means things like ants and peas and dollhouse and tables.”

So, no matter how good the AI is at reading, how good it is in math, it still writes laughable answers. So, conflating computers in education, AI systems in education, and the mind still creates an oxymoron.

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Responsible decision making in the use of artificial intelligence from students' perspective

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Abstract

Responsible decision making in the use of artificial intelligence (AI) has been one of the key issues in recent years. With technological development progressing faster than ever and no formal regulations yet in place, young people must often rely on their judgement and critical thinking. The aim of this study was to determine students' perspectives on the use of AI in lectures, as well as on AI and social and emotional skills as transversal competencies. The written responses of the 49 university students (pre-service early childhood education teachers) on the topic of responsible decision making and the use of AI were analysed. The main findings show that students are aware of the potential of AI use and are quite enthusiastic about the potential of AI in problem solving, reasoned judgement and evaluation. However, they also reported concerns relating to trust, accuracy, addiction to AI, the impact on personal development, i.e. AI is unable to predict and assess consequences or impacts due to the complexity of human life. The study is important because it provides insight into students' perceptions of important themes related to responsible decision making in the use of AI.

Key words: social and emotional skills, responsible decision making, artificial intelligence, students' perspectives

Introduction

Responsible decision making is an integral component of social and emotional learning (SEL), which has become increasingly central to education due to demand from educators, parents, students and business leaders, as well as rigorous research showing broad, positive impacts for students and adults (Mahoney et al., 2021). The Collaborative for Academic, Social, and Emotional Learning (CASEL), a movement committed to making SEL an integral part of education, emerged from a small conference in 1994. At that time, both CASEL and the term 'social and emotional learning' were born. Today, there is unprecedented momentum for an educational system that fully supports students' social, emotional and academic learning. As the SEL movement continues to grow, the demand for clear guidelines, evidence-based practices, and continuous learning has never been greater (CASEL, n.d. – a). Specifically, social and emotional education programmes improve students' abilities to coordinate emotions, cognition and behaviour so that they can effectively and ethically handle developmentally appropriate tasks (Graczyk et al., 2000). To promote healthier and safer behaviour in young people, it is important to support the development of new information, attitudes and skills in an ever-changing environment (Van Huynh et al., 2023).

Today, SEL is defined by CASEL (2020) as: ‘Social and emotional learning (SEL) is an integral part of education and human development. SEL is the process through which all young people and adults acquire and apply the knowledge, skills and attitudes to develop a healthy identity, manage emotions and achieve personal and collective goals, feel and show empathy for others, establish and maintain supportive relationships, and make responsible and caring decisions. SEL promotes educational equity and excellence through authentic school, family and community partnerships to establish learning environments and experiences that feature trusting and collaborative relationships, rigorous and meaningful curriculum and instruction, and ongoing evaluation. SEL can help address various forms of inequity and empower young people and adults to co-create thriving schools and contribute to safe, healthy and just communities.’

The CASEL model can be taught and applied at various developmental stages from childhood to adulthood and across diverse cultural contexts. CASEL addresses five broad and interrelated competence domains and highlights examples for each domain: self-awareness, self-management, social awareness, relationship skills and responsible decision making, e.g. ethical and principled choices in personal and social situations (CASEL, n.d. – b). In their meta-analysis of school-based SEL interventions, Durlak et. Al (2011) found that participants demonstrated significantly improved social and emotional skills, attitudes, behaviour and academic performance. They also improved students’ behavioural adjustment in the form of increased prosocial behaviour and reduced conduct and internalising problems, as well as better academic performance in achievement tests and grades. Therefore, these skills also relate to a lower incidence of risk behaviours in life.

Responsible decision making is one of the essential competencies for making responsible decisions in life and also reasonable attitudes related to AI. Responsible decision making is defined by CASEL (n.d. – b) as: ‘The ability to make caring and constructive choices about personal behaviour and social interactions across diverse situations. This includes the capacity to consider ethical standards and safety concerns and to evaluate the benefits and consequences of various actions for personal, social and collective wellbeing.’

Responsible decision making also relates to problem solving, reflecting on one's biases and character (Mahoney et al., 2021). Making responsible decisions also requires the ability to recognise when individuals have made the correct or incorrect choice and taking responsibility for the consequences of those choices (Van Huynh et al., 2023), which is becoming increasingly important due to the rapid development of AI systems in everyday life. The rapid expansion of AI makes it necessary to promote AI education. However, educating young learners to become AI-competent citizens poses a number of challenges (Zhang et al., 2023) and could partly be addressed by developing social and emotional competencies and responsible decision-making skills.

While existing SEL learning processes are successful in helping students develop their reflective abilities to some extent, previous work on supporting reflection in human-computer interactions suggests that digital technology has the potential to further extend and complement such training. For example, the classroom context of a SEL lesson is likely to be particularly well suited for initial exploration of technology, as it allows the development of real-life scenarios, albeit in a relatively limited and manageable environment (Slovak & Fitzpatrick, 2015).

While AI systems require the competence to make responsible decisions, they can also help to make data-driven decisions and develop personalised interventions that meet individual learning needs by providing real-time feedback and deep insights into students' strengths and weaknesses. By fostering a critical mindset that balances the benefits of AI with its potential harms, educators can promote responsible use of AI to mitigate adverse societal consequences (Kamalov et al., 2023). In order to responsibly integrate AI into the educational process, the views and attitudes of future teachers (and especially early childhood education teachers in particular) are crucial. In a large-scale study in Sweden, students expressed a generally more positive attitude towards AI language tools for educational purposes compared to chatbots such as ChatGPT. The results also indicate widespread adoption of AI language tools and fewer concerns related to their use (Malmström et al., 2023).

It is important for university teachers to understand students' prior knowledge, experience, perspectives and resources to support them in gaining knowledge and insights about the use of AI as a current and future technology (Tatar et al., 2022), which was the overall aim of this study. By actively supporting young people to broaden their perspectives beyond themselves and their social circles, educators can empower them to address global issues with social and emotional skills, such as the responsible use of AI (Chowkase, 2023).

The purpose of the study was to analyse students' understanding of responsible decision making from the perspective of the use of AI. The overall aim was to support students in gaining information and insights about the use of AI as a current and future technology (Tatar et al., 2022), assess students' prior knowledge, experience and viewpoints, and encourage them to reflect on their viewpoints on the use of AI tools and systems.

The research questions of this study are:

1) Which dimensions of responsible decision making related to the use of AI were most often reported in students' perceptions?
2) What do students understand by responsible decision making when using systems or tools that incorporate artificial intelligence?
3) What concerns do students have about the use of artificial intelligence?

Method

Participants and data collection

The study involved 49, 2nd year students attending a full-time Early Childhood Education study programme at the Faculty of Education at the University of Maribor, Slovenia. The students are aged between 20 and 23. Of the total number, 46 women and 3 men.

The study participants were informed about the purpose of the study and their participation.

Data was collected using the written responses of the students in the groups related to the task during the *Didactics of Introduction to the Social Environment* course. In the classroom, the students voluntarily formed ten groups, each with four or five students, to discuss specific questions and come up with answers related to the learning task based on the consensus in the group. The leader of the group was tasked with uploading the answers related to the task to the e-learning platform at the end of the course. After uploading the written answers, the students presented their ideas and discussed them with the other groups and the teacher.

Prior to the learning task, the teacher gave the students a 90-minute introduction to the CASEL model of social and emotional skills (de Paoli et al., 2017). Data collection was based on the task given to the students during the workshop after the lectures. The task was to discuss in groups the various possibilities of using

AI and situations in which it can be used, and to try to define how various tools or systems that involve AI can be using in terms of the dimensions of the CASEL model of responsible decision, as shown below:

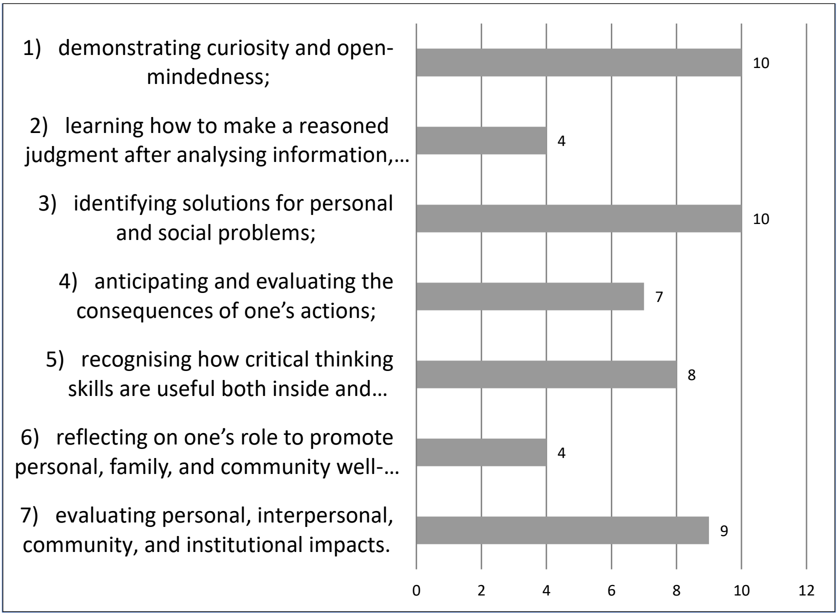
- demonstrating curiosity and open-mindedness
- learning how to make a reasoned judgment after analysing information, data, and facts
- identifying solutions to personal and social problems
- anticipating and evaluating the consequences of one's actions
- recognising how critical thinking skills are useful both inside and outside of school
- reflecting on one's role to promote personal, family and community well-being;
- evaluating personal, interpersonal, community and institutional impacts).

The students prepared written answers in the groups taking into account the dimensions of responsible decision making.

To qualitatively analyse the written texts for this task, the authors used open coding and axial coding (Corbin and Strauss, 1990). The open coding method was used to analyse the written text. The text was coded, and similar codes were classified under a common concept. An open coding analysis was carried out on the text, whereby the authors first analysed the codes and classified them into concepts. Axial coding was used in the next step of the analysis. A comparison was made of codes and concepts, which were then categorised into broader categories, as shown in the results (Corbin and Strauss, 1990; Flick, 2006) according to the CASEL dimensions for responsible decision making. The coding process was carried out using Atlas.ti software (version 22).

Results

Figure 1
Number of student responses for the dimensions of responsible decision making



The results indicate that the majority of students were able to come up with some reflections on how AI can be used to promote curiosity and open-mindedness, identify solutions to personal and social problems, and evaluate personal, interpersonal, community and institutional impacts. However, after analysing the information, data and facts, only four out of the ten groups were able to indicate how the use of AI can support reasoned judgement and promote personal, family and community wellbeing, which suggests that they do not fully understand the role of AI in supporting critical thinking and reasoned judgement as well as its role in promoting human wellbeing.

The results below illustrate an analysis of students' answers together with some quotes for the categories in the themes.

Table 1
Analysis of students' answers about how the use of AI can influence human curiosity and open-mindedness

Theme	Category	Code
Curiosity and open-minded-ness (16)	Pros for curiosity and open-mind-edness (10)	AI stimulates curiosity (6)
		AI can support learning (4)
		AI can help to find answers (3)
		AI can support humanity (3)
		AI can support development of new technologies (3)
		AI can support personalised learning (2)
		AI saves time (2)
		AI can support interactive learning (VR) (1)
		AI can support open-mindedness (1)
		AI can support creativity (1)
	Cons for curiosity and open-mind-edness (3)	AI can decrease open-mindedness (3)
		AI is not reliable (1)
		AI can decrease human thinking (1)
	Other (3)	Critical evaluation of AI answers needed (4)
		Children should be taught about AI (1)
		AI should be used safely and with good purpose (1)

The analysis of the students' responses related to the assessment of how AI can influence human curiosity and open-mindedness shows that most arguments are in favour of using AI. The most common ideas are that AI can stimulate curiosity, support learning, help find answers, support humanity and the development of new technologies.

“We believe that AI is gaining ground in personal life and education, as it has great potential to enhance learning and develop curiosity and open-mindedness.” (G8)

Some groups of students also presented arguments against the use of AI. These arguments relate to the decrease in human thinking ability and open-mindedness and that AI is not reliable.

“AI satisfies curiosity by more quickly finding answers to the different questions in which you are interested, however, it limits your answers because you are satisfied with the answer you are given and do not think further, showing no open-mindedness.” (G5)

Students also frequently mentioned the need for critical evaluation of the information generated by AI, suggesting that they are aware of the potential pitfalls of using AI. For example:

“We need to critically evaluate the information we obtain, as not all sources are reliable. This requires data and information analysis. This means not believing everything we read straight away but trying to obtain more information from different sources. This helps us to judge whether or not the information we have obtained is true”. (G7)

Table 2
Analysis of students' answers about how the use of AI can influence human learning related to reasoned judgment after analysing information, data and facts

Theme	Category	Code
Learning related to reasoned judgement (9)	Pros for AI and reasoned judgement (3)	AI can support reasoned judgement in education (IEP, learning objectives, knowledge) (2)
		AI can support human reasoned judgment (1)
		AI can support analysis of a large amount of data (1)
	Critical thinking needed (6)	AI should not be the only source of information (2)
		Communication for reasoned judgment is needed (1)
		Critical judgment of information is needed (1)
		Knowledge about information is needed (1)
		Thorough analysis of data is needed (1)
		Reasoned judgment should include various scenarios (1)

The analysis of students' responses related to the assessment of how AI can influence human learning in the context of reasoned judgement after analysing information, data and facts shows that students resonate that AI can support reasoned judgement in education, especially teachers' reasoned judgement in the individualised planning of instruction for students with special educational needs, planning of learning objectives and acquisition of knowledge in the context of classroom instruction. The students also recognised that AI can analyse large amounts of data, which can be useful for reasoned judgement.

"AI systems can help in education, for example, by using personalised learning programmes based on an analysis of an individual's abilities and needs. This enables teachers and tutors to help students achieve their goals and prepare for the future more effectively." (G10)

However, the critical thinking in the students' views in relation to learning with AI as a source of information for making reasoned judgement is quite clear and prevails according to the number of the codes in categories. Students reported that AI should not be the only source of information. They also reported that they would prefer to learn with the support of others through communication, data analysis, scenarios and critical judgement of information.

Table 3
Analysis of students' answers about how the use of AI can influence the identification of solutions to personal and social problems

Theme	Category	Code
Identifying solutions for problems (29)	Pros related to problem solving with AI (4)	AI can support problem solving (7)
		AI can improve life quality (2)
		AI can predict consequences (1)
		AI can support personal development (1)
	Cons related to problem solving with AI (6)	AI decreases personal and social relationships in problem solving (1)
		AI increases addiction to AI in problem solving (2)
		AI should not replace friends' support in problem solving (1)
		AI should not replace professional support in problem solving (1)
		AI solutions to problems are too general (1)
		AI can decrease creativity in problem solving (1)
	Other Ideas (2)	Ethical issues in problem solving should not be neglected (1)
		Professionals and AI should work together to solve problems (1)
	Problems that can be solved with the support of AI (17)	AI can be used for the development and use of new technologies (1)
		AI can be used for environmental problem solving (2)
		AI can be used for space research (1)
		AI can be used in the development of strategies for problem solving (1)
		AI can be used in the economy (development of new products and services) (1)
		AI can be used in employment problems (1)

	AI can be used in epidemic and pandemic problem solving (1)
	AI can be used in social interactions problems (dating apps) (1)
	AI can find solutions for better educational systems (1)
	AI can find solutions for equal opportunities in education (1)
	AI can find solutions for personalised learning (2)
	AI can find solutions in access to education (1)
	AI can support problem solving in education (1)
	AI can solve logistic problems (1)
	AI can solve problems in medicine (4)
	AI can support financial problem solving (2)
	AI can support in social problem solving (poverty, unemployment, discrimination…) (1)

The analysis of the students' responses related to the assessment of how AI can influence the identification of solutions to personal and social problems shows that the largest number of ideas can be found in the category where students listed the problems that could be solved with the support of AI. Nine different general human problems (development of new technologies and development of the economy, as well as environmental, employment, epidemic/pandemic, social interaction, logistic, medical and social problems) were identified, as well as four specific problems in the field of education (education systems, equal opportunities in education, personalised learning, access to education). Problems in the areas of medicine, environment and the economy were mentioned most frequently. These results indicate that students are able to recognise and are very aware of the problems of modern human life and that they believe that AI can be a supporting technology in solving the aforementioned problems.

“AI systems can help find solutions for sustainable development, for example, by using data to monitor and predict environmental pollution, climate change and the exploitation of natural resources. It can help predict trends and develop new products and services based on data on purchasing habits and other factors. It can help improve healthcare by analysing health data, which can reveal patterns and help in the diagnosis and treatment of diseases.” (G10)

“In personal life, AI could help with a variety of tasks, especially analysing health data, recommending medicines, adapting lifestyles or finding the best ways to save money. AI can also help solve a variety of everyday problems, such as finding the nearest shop or restaurant, ordering food or booking airline tickets.” (G8)

In terms of the general arguments in favour of and against the use of AI for solving problems, it can be determined that students are more inclined towards the use of AI. The statements ‘AI can support problem solving’, followed by ‘AI can improve the quality of life’ received the highest number of codes.

“In addition, AI can also be used to develop and deploy new technologies that can help tackle societal problems such as pollution, climate change (…) and improve quality of life.” (G10)

Critical thinking can be identified within this theme, as the respondents reported that AI can increase dependence on AI in problem solving and decrease human creativity in problem solving, and that AI should not replace the support of friends or decrease personal and social relationships in problem solving. They also argued that AI should not replace professional support.

“Our opinion is that AI should not be used to solve our personal problems, as it cannot replace genuine contacts with people (friends, people we trust). A person who knows us can advise us better than an app, as they really know our situation, our personality and how we react to emotions.” (G8)

Table 4
Analysis of students' answers about how the use of AI can support the anticipation and evaluation of the consequences of one's actions

Theme	Category	Code
Anticipation and evaluation of the consequences (21)	Pros related to the anticipation and evaluation of the consequences of the use of AI (2)	AI can support the anticipation and consequences of one's actions (6) AI can support responsible decision making of one's actions (1)
	Cons related to the anticipation and evaluation of the consequences of the use of AI (4)	AI cannot explain the consequences of one's actions (2) Consequences should be predicted by professionals (1) Consequences should be predicted with human reasoning (2) AI cannot include all emotions, situations and problems when evaluating consequences (1)
	Other Ideas (3)	Anticipation and evaluation of actions can prevent undesired consequences (1) People should know how to use AI for the purpose of anticipating consequences (2) Anticipation and evaluation of consequences is important (2)
	Consequences that can be anticipated and evaluated with the support of AI (12)	Consequences in education (2) Consequences of technology use in education (2) Consequences in work with SEN children (1) Consequences in use of teaching methods (1) Consequences in the use of technology (safety on the internet, use of time, addictions to technology) (2) Consequences in personal life (1)

	Consequences of environmental problems on the economy (2)
	Consequences of financial decisions (1)
	Consequences of one's habits (1)
	Consequences of political decisions (1)
	Consequences of social interactions (1)
	Consequences for health (2)

The analysis of the students' responses in relation to the evaluation of how AI can support the anticipation and evaluation of the consequences of one's actions indicates that the largest number of ideas can be found in the category in which the students list the consequences that can be anticipated and evaluated with the support of AI. They identified one general and three specific consequences in education (use of technology, working with SEN children, and teaching methods) that could be anticipated and evaluated with the support of AI, although discussion with students showed that they did not know exactly which AI tools could be used for this purpose.

> *"In education, however, anticipating and assessing the consequences of our actions when using AI can help us choose the right tool or technology to help us achieve our desired goals." (G8)*

The students also identified seven consequences related to general problems of humanity (technology use, personal life, environment, economy, lifestyle, political decisions and health).

> *"AI can help assess the environmental consequences of our actions, for example, by predicting the impact on climate change and recommending sustainable solutions." (G10)*

The students' arguments for and against in terms of anticipating and evaluating the consequences of the use of AI are quite similar in terms of the number of codes, although the con arguments have a greater number of various codes indicating that the consequences should be anticipated with human reasoning and professionals and that AI is unreliable and cannot include all the complexities of human behaviour when assessing the consequences.

An example of students' arguments against the use of AI in predicting consequences:

"Artificial intelligence can help to predict different scenarios and calculate the likely consequences, thus helping in making more informed and meaningful decisions." (G8)

An example of students' argument against the use of AI in predicting consequences:

"AI cannot predict or assess the consequences of our actions, which can only be best assessed by us." (G6)

Table 5
Analysis of students' answers about how the use of AI can support the use of critical thinking skills (CTS) inside and outside of school

Theme	Category	Code
Critical thinking skills (CTS) (28)	Characteristics of critical thinking and CTS (8)	Critical thinking is being capable of objective reasoning (2)
		Critical thinking can be supported by scientific knowledge (1)
		Critical thinking can be improved by making mistakes (1)
		Critical thinking is crucial in the use of information resources (3)
		Critical thinking is a human domain (not AI) (1)
		CTS can be used for problem solving (4)
		CTS can be developed (1)
		CTS should include ethical and moral values (1)
	Purposes of CTS within the use of AI (8)	CTS can be used for responsible decision making (7)
		CTS are needed for reading the news in media (1)
		CTS are needed in information research (1)
		CTS are needed to recognise fake news (1)

	CTS are needed to recognise false data or info (3)	
	CTS are needed on social networks (1)	
	CTS are needed to recognise true/false arguments (2)	
	CTS are needed to recognise the intentions of information (1)	
	Code	**Subcode**
Purposes of critical thinking (general) (8)	CTS can be used in school (4)	CTS are needed for writing (2)
		CTS are needed for reading (2)
		CTS can help to understand how others think and why (1)
		CTS are needed for successful education (1)
	CTS can be used outside school (4)	CTS are needed for communication (1)
		CTS are needed for making decisions in a globalised world (1)
		CTS are needed in a tolerant and inclusive society (1)
		CTS are needed to adapt to changes in the world (1)
Critical thinking vs. AI (4)	We cannot trust all info on the internet (1)	
	AI cannot support critical thinking (3)	
	AI can support critical thinking (4)	
	AI can support understanding of a multicultural society which is important for CT (1)	

The analysis of the students' responses in relation to reflections on how AI can support the use of critical thinking skills inside and outside of school indicates that students reported several ideas relating to how and why AI can be used in school (sub-codes: for reading, writing, understanding and successful education) and outside school (sub-codes: for communication, decision making, tolerance and the ability to adapt to change). There was a higher frequency of reported ideas in terms of how CTS can be used in school in comparison to how it can be used outside of school.

"In education, AI can help to identify how critical thinking skills are useful in different subjects and how teachers can integrate them into the curriculum. For example, it can help develop critical reading and writing skills, which are crucial for successful studying and also in everyday life. Artificial intelligence can also help to develop the ability to critically evaluate and assess different arguments and to recognise different perspectives on different issues." (G8)

The students argued that critical thinking skills are essential when using AI. Their arguments mostly related to the potential pitfalls or misinformation when using AI, e.g. reading news in the media, recognising fake news, true/false arguments, the intentions of information, information research, etc. The most frequently cited argument was that CTS can be used for responsible decision making in the context of AI use.

"AI can produce a large amount of information, but this does not necessarily mean that all the information is reliable and true. Critical thinking skills help us to recognise and evaluate the quality of the information we receive. Algorithms can include biases that can lead to unfair decision making. Critical thinking can help us to identify bias." (G10)

Interestingly, most groups also felt the need to define the characteristics of critical thinking and critical thinking skills in their written reflections. This allows the conclusion to be drawn that they are able to define critical thinking as an ability to reason objectively, as a human (non-AI) domain, that critical thinking can be supported with knowledge, and that it is a process-based skill that can be learnt, developed and used to solve problems, etc.

"Critical thinking is the ability and willingness to evaluate claims and make objective judgements based on well-supported arguments." (G1)

Some other codes also appeared in this theme that are in the category of critical thinking vs AI. There are two opposing arguments: AI can and cannot support critical thinking, and again students report critical reflection in terms of not trusting information on the internet.

Table 6
Analysis of students' answers about how the use of AI can promote personal, family and community wellbeing.

Theme	Category	Code
AI and wellbeing (25)	Personal wellbeing (18)	AI apps can increase productivity (1)
		AI apps (chatbots) can give financial advice (1)
		AI apps can decrease stress levels (1)
		AI apps can support a healthy lifestyle (1)
		AI apps for meditation are useful (1)
		AI apps for motivation are useful (1)
		AI apps for self-help are useful (1)
		AI apps to support personal wellbeing are useful (1)
		AI can analyse habit data to support wellbeing (1)
		AI can analyse health data to support wellbeing (1)
		AI can analyse interactions on social media to support wellbeing (1)
		AI can analyse lifestyle data to support wellbeing (1)
		AI can analyse professional development data to support wellbeing (1)
		AI can analyse educational data to support wellbeing (1)
		AI can provide suggestions for joining associations and clubs (1)
		AI can suggest personalised advice to support health and wellbeing (1)
		AI platforms can improve our knowledge and skills on a personal level (1)
		The support of AI can help us develop the ability to understand and tolerate others (1)

	Family well-being (4)	AI apps can give advice for family life (1) AI can support communication in families (long-distance) (1) AI platforms can support financial decisions (1) AI smart houses can optimise processes (temperature, safety, lighting) (1)
	Community wellbeing (3)	AI can support communication in communities (1) AI can support community wellbeing if decisions are data based (1) AI can support education and learning (1)

The results of the analysis on the theme of wellbeing indicate that the students most frequently mentioned ways in which AI could support personal wellbeing. Interestingly, they had very different ideas. Eight of the respondents involved the use of apps (to increase productivity, for financial advice, to reduce stress levels, support a healthy lifestyle, meditation, motivation, self-help, etc.), while six of the ideas related to analysis of data that can be used to support wellbeing (habit data, health data, social media interaction data, lifestyle data, education data, career development data). Some ideas for supporting personal wellbeing also include AI advice and services.

"There are many applications that can help us improve our mental and physical health by using AI technology. Meditation, self-help and motivation apps can help us reduce stress, improve productivity and maintain a healthy lifestyle. If we are looking for advice or solutions to the challenges we are facing, we can use chatbots to offer suggestions to solve problems. Chatbots can offer advice and information on a variety of topics such as health, finances, family life and more." (G10)

Compared to the personal wellbeing category, the students reported fewer ideas in the family and community wellbeing category. For family wellbeing, they reported that AI apps can give advice on family life and support communication between family members who live far apart. In addition, apps can make financial decisions for the family and build smart homes where AI can optimise the processes of living in homes. For community wellbeing, students reported that AI can support communication and decisions in communities, education and learning.

“Smart homes use artificial intelligence to automate processes and improve home comforts. These systems can help control temperature, lighting, security and other aspects of our homes.” (G10)

“AI I can help us keep in touch, provide us with ideas for activities for participating in different associations or communities. By building relationships with other people, we can develop the ability to recognise other people’s points of view, understand social and ethical norms in different settings, and learn to respect others.” (G7)

Table 7
Analysis of students’ answers about how AI support can be used to evaluate personal, interpersonal, community and institutional impacts

Theme	Category	Code
Impact evaluation (21)	Characteristics of impact evaluation (11)	Evaluation of impacts is very complex (2)
		Evaluation of impacts improves results (1)
		Evaluating institutional impacts is important for responsible decision making (2)
		Evaluating interpersonal impacts is important for responsible decision making (1)
		Evaluating community impacts is important for responsible decision making (1)
		Evaluating personal impacts is important for responsible decision making (1)
		Evaluation is important for informed and responsible decision making (1)
		Evaluation of impacts increases the understanding of problems (1)
		Evaluation should include environmental, ethical, social and economic perspectives (1)
		Evaluation should include knowledge, critical thinking and analyses (1)
		Humans are responsible for the impacts (1)

	AI and impact evaluation – pros (8)	AI can evaluate impacts (1) AI can evaluate the institutional impacts of society (3) AI can evaluate interpersonal impacts (1) AI can evaluate the impact of education (1) AI can evaluate impacts on personal life (2) AI can evaluate community impacts (1) AI can analyse bias in impact evaluation (1) AI can support humans in understanding impacts (1)
	AI and impact evaluation – cons (2)	AI cannot evaluate total impact due to the complexity of human life (1) AI systems can decrease human ability to evaluate impacts (1)

The results of the analysis on the theme of the evaluation of impacts indicate that students most frequently mentioned the characteristics of impact evaluation on personal, interpersonal, institutional and community levels. They reported that these evaluations are highly complex and important in terms of responsible decision making, while they also increase understanding of problems and involve multiple perspectives (environmental, ethical, social and economic) and processes (critical thinking and analyses).

"Assessing personal, interpersonal, community and institutional impacts is the process of gathering information and analysing the effects that different factors have on individuals, communities and institutions. This process is very complex and can help to understand how different factors affect an individual or community and how they can be changed or improved for better outcomes. Artificial intelligence can be used to assess personal, interpersonal, collective and institutional impacts in a variety of ways." (G7)

The students' arguments for and against the use of AI for impact evaluation are in favour of the use of AI at all of the above levels. However, in the 'against' arguments, they state that AI cannot perform evaluations of impacts due to the complexity of human life and can also limit human ability to evaluate impacts.

Discussion

Analysing students' perceptions of AI is crucial in effectively integrating AI into higher education and avoiding potential pitfalls (Kim et al., 2023; Tatar et al. 2022). When students understand AI, it can lead to more informed use, a better understanding of the possibilities and importance of AI technologies (Druga et al., 2019), the use of AI to solve problems (Kong & Abelson, 2022), and more responsible decision making as one of the key concepts of social and emotional competencies. It is important for university teachers to understand students' prior knowledge, experience, perspectives and resources to support them in gaining knowledge and insights about the use of AI as a current and future technology (Tatar et al., 2022), which was the overall aim of this study. By actively supporting young people to broaden their perspectives beyond themselves and their social circles, educators can empower them to address global issues with social and emotional skills, such as the responsible use of AI (Chowkase, 2023).

Our research shows that students better understand responsible decision making when using AI when it comes to simpler or more general areas of responsible decision making. Most groups reported more ideas and were confident in asking whether AI can support humans in demonstrating curiosity and open-mindedness, identifying solutions to personal and social problems, and evaluating personal, interpersonal, community and institutional impacts. However, only four out of the ten groups were able to indicate how the use of AI can support reasoned judgment and promote personal, family and community wellbeing. This suggests that they may not yet fully understand or grasp the role that AI plays, or could play, in promoting human wellbeing and supporting critical thinking and sound judgement. Seemingly, the study by Chan and Hu (2023) suggests that students' attitudes towards more subtle applications of AI are more ambivalent.

The students expressed both enthusiasm and concerns in all the themes of responsible decision making. The results also highlight the potential benefits and risks associated with the use of AI, which are perceived differently by students. Students' arguments about responsible decision making reflect a fairly good understanding of the pros and cons of using AI technologies and a predominantly positive attitude towards using these technologies in learning, personal life, family and community. Similar results can also be found in other studies (Santomartino & Yi, 2023; Busch et al., 2023).

The most common ideas are that AI can stimulate curiosity, support learning, help find answers, support humanity and the development of new technologies.

Students recognised that AI can analyse large amounts of data, which can be useful for reasoned judgement in various ways, especially in education for reasoned judgement in individualised planning of instruction for students with special educational needs, planning of learning objectives and acquisition of knowledge in the context of classroom instruction. Students were also quite optimistic about the ability of AI to solve problems. They expressed the belief that AI can be an assistive technology in solving problems. Students recognise the potential of AI in supporting human curiosity, reasoned judgement, identifying solutions to problems, evaluating consequences, supporting critical thinking skills, promoting wellbeing and evaluating impacts, as stated in the study by Chan and Hu (2023).

The concerns expressed by the students in relation to responsible decision making when using AI are that it is not reliable, can limit human thinking and creativity, should not be the only source of information, and that critical judgement of information is urgently needed. They also expressed concern that the use of AI in various areas can be addictive and that it is unable to predict and assess the consequences or impact due to the complexity of human life. Based on the number of codes and conversations with students after completing the assignment, it can be concluded that the students are partially aware of concerns relating to AI, as they did not mention important concerns that will hopefully be regulated in the future (e.g. AI systems that exploit certain vulnerable groups such as people with intellectual disabilities, that AI systems can be used by authorities for social scoring purposes or the use of real-time biometric identification systems in public spaces) (Artificial Intelligence Act: deal on comprehensive rules for trustworthy AI, 2023).

This study provides insightful information about students' perceptions of AI from the perspective of responsible decision making. It highlights the need for continued study and curriculum development to help students develop responsible, knowledgeable and critical thinking behaviour as AI users.

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Synergy of Beliefs between Social-Emotional Learning and the Use of Artificial Intelligence Systems in Schools: A Cluster Typology Analysis among Students

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Abstract

Today's remarkable technological development challenges the teaching profession to develop new approaches to meet student needs for living in a rapidly growing digital society. The functionality of teachers becomes crucial, particularly related to their transversal competencies, such as the competence in using artificial intelligence (AI) systems and competence in developing social-emotional learning (SEL) in students. In this study, we were interested in the synergy between SEL beliefs and attitudes towards AI in teaching from the perspective of students (pre-service teachers). An empirical, quantitative online survey was conducted on 328 university students in pedagogical study programs (80.2 % female, M_{age}=21.55 years). The findings showed that students assessed themselves as more competent in using SEL than AI in teaching. Hierarchical cluster analysis revealed three groups of students related to the SEL and AI synergy, such as "SEL & AI advocates", "SEL believers & AI sceptics", and "SEL & AI sceptics". The findings of this study are significant for the understanding that SEL can significantly contribute to innovative thinking about the use of AI in schools and its integration into human lives.

Keywords: pedagogical students, social-emotional competencies, digital competencies, hierarchical cluster analysis

Introduction

In today's rapidly changing and developing society, teaching demands various novel competencies to meet student needs. The current rapid technological leap requires development of new approaches to boost students' digital competencies. At the same time, the new era of digitalization is changing the means of communication and social relationships in schools, extracurricular activities, and families, severely impacting students' social-emotional competencies. Undoubtedly, social and emotional skills and competencies, which are among the priorities in educational policy of the 21st century, have been challenged by technological change, development and the ethics of AI (Tuomi, 2022). With the challenges and opportunities of an uncertain future, educators must adapt their pedagogy and didactics to meet the needs of their students (Mori, 2023).

From the perspective of teachers' responsibilities and their essential role in education, the functionality of their competencies is crucial, particularly in relation to transversal competencies such as competence in using artificial intelligence

(AI) systems and competence in developing social-emotional learning (SEL) in students.

AI competencies in teaching

Teachers' attitudes towards AI play an essential role in acceptance (or non-acceptance) of AI in their teaching and everyday life. In general, there still exists a complex of mixed feelings towards AI, with individuals recognising the social benefits of using AI while experiencing negative emotions such as fear and anxiety related to the risks of AI (Luckin et al., 2022; Schepman & Rodway, 2020). Therefore, AI technologies should be developed responsibly − slowly, safely and securely, and particularly in the public interest (Luckin et al., 2022). There is a need to move beyond AI-centric views, focusing merely on the ability to use AI and, more broadly, to consider the cognition of technology, social interaction, and values (Markauskaite et al., 2022). AI literacy should be understood as "a set of competencies that enable individuals to critically evaluate AI technologies, communicate and collaborate effectively with AI, and use AI as a tool online, at home and in the workplace" (Long and Magerko, 2020, p. 1).

An overview of study programmes and reports on the forecasting of the digital workforce defined three profiles of digital competencies that need to be addressed to successfully manage the digital challenges in the workplace: pure digital profiles, supporting digital profiles and non-digital profiles (Lipovec et al., 2020). In this study, the teaching staff was defined as pertaining to the non-digital profile. Non-digital profiles are profiles that work with digital tools but use these mainly as a tool for achieving other working goals. These profiles are expected to reach the minimum digital competencies in information literacy, communication and collaboration, and security. For non-digital profiles, the authors recommended at least one independent course in ICT learning, with digital content and basic digital skills as part of the core transferable skills included in their teacher education (Lipovec et al., 2020). Markauskaite et al. (2022) pointed out that digital literacy should be developed through teaching approaches such as explicit teaching, authentic learning, critical thinking, reflective practices and AI-mediated learning.

SEL competencies in teaching

The socio-emotional competencies are defined as those competencies related to responsible decision-making, social awareness, self-management, self-awareness, social relations skills, and cooperative learning (Chen et al., 2021; Collie et al., 2015) and can be developed through social-emotional learning (SEL), which is “*the process through which children and adults acquire and effectively use the knowledge, attitudes and skills needed to understand and manage emotions, set and achieve goals, experience and show empathy for others, establish and maintain positive relationships, and make responsible decisions*” (Bartlett, 2019, p. 7). SEL can be empowered through (1) fostering self-knowledge, self-esteem, and respect for others among students (self-awareness, social awareness); (2) developing behaviours that allow students to perceive and express feelings and self-regulating emotions (self-control); and (3) developing assertive communication skills aimed at improving conflict resolution (relational skills, responsible decision-making) (Bartlett, 2019; Santamaría-Villar et al., 2021).

Although most studies have shown directly related positive effects of SEL programs in producing positive outcomes in social-emotional competencies among students (Bartlett, 2019; Collie et al., 2015; Santamaría-Villar et al., 2021), some studies have pointed out that the quality of the SEL programs implemented in schools could vary widely and consequently could have a negative impact on the program’s effects. Influencing factors that differentiate between the high and low implementers of SEL programs was found to be related, among other factors, to the teacher and school context (Dowling & Barry, 2020).

SEL is an important factor influencing how students learn and perform in school and should therefore be an integral element of any curriculum at all levels of education in any school system (Bartlett, 2019). Teaching SEL in schools could significantly contribute to the development of socio-emotional skills and competencies and consequently to creation of a climate of cooperation in the classroom with less disruptive behaviour, such as conflict, violence and abuse (Santamaría-Villar et al., 2021). Besides improving students’ prosocial behaviour, SEL significantly contributes to their academic achievements (Collie et al., 2015). Moreover, teacher’s own beliefs about SEL have a significant predictive role in a positive relationship with the group. Teachers’ difficulties in establishing a good educational relationship with children can also be explained by their lower capacity to perceive, understand, and manage emotions (Poulou, 2017). Therefore, it is essential to strengthen the social-emotional competencies not only in children but also in teachers.

Not all teachers have equally positive beliefs about SEL in teaching students. These are often related to their own social-emotional competence and general beliefs about SEL in school. An empirical study on a sample of Canadian teachers (80 % female, M_{age}=44.9 years, 77 % from elementary school) showed three different latent groups of teachers according to their SEL beliefs: 1) SEL implementers (high beliefs and commitment, environmental support), 2) SEL promoters (high beliefs and commitment, low environmental support) and 3) SEL advocates (high commitment, low beliefs and environmental support). The most positive beliefs were reported by teachers with the profile of SEL implementers, who were highly committed to SEL and had high support from the school environment (Collie et al., 2015).

Synergy between SEL and AI

In synergy between SEL and AI, an established field of studies that analyses the impact of one of the components (SEL or AI) on the outcomes of another can easily be recognized. In most cases, the outcome of using AI to increase SEL or using SEL to improve the efficiency of AI use is positive. For example, a study by Chen et al. (2021) addressed the association between SEL and problematic Internet use among 1141 high school students from Southwest China. Using structural equation modelling while controlling for demographic factors, the study found that overall SEL competence and all individual SEL domains had a significantly negative association with problematic Internet use. The study by Prentice et al. (2020) on improving organisational performance-related outcomes concluded that human social-emotional intelligence, compared to AI, has a dominant impact on employees, especially in professions that require working with people. However, at the same time, this study found that AI plays a moderating role in the relationship between social-emotional intelligence and behaviour outcomes. SEL contributes to self-regulated learning, performing cognitive work where AI is less capable, creativity, responsibility in using AI, creating AI for humanistic values, and collaborative thinking. Markauskaite et al. (2022) divided the benefits of SEL to the use of AI into three perspectives: humanistic (e.g. human-centred AI, humanistic values and freedoms), social perspective (e.g. AI-mediated dialogue, networked learning) and cognitive perspective (e.g. creativity, self-regulation, hybrid cognition).

On the other hand, the use of AI or other advanced technologies in the classroom was found to have an important impact on SEL and overall learning outcomes (Salas-Pilco, 2020) and on building and strengthening prosocial behaviours and interactions with peers (Guilbaud et al., 2022) by the development of an integrated learning framework, which considers a broader spectrum of human potential and enhances students’ academic experience in a more integral, inclusive and emotionally supportive learning environment.

In the literature, it is possible to find studies analysing teacher attitudes either towards SEL (Brackett et al., 2012; Collie et al., 2015) or towards AI (Gatlin, 2023; Schepman & Rodway, 2020). However, there is a lack of studies addressing the synergy of beliefs about SEL and AI systems in the teaching profession.

Empirical study

Based on the presented theoretical overview, we decided to look more closely at synergy between SEL and the use of AI in schools. We were particularly interested in beliefs about and attitudes towards SEL and AI in teaching from the perspective of university students who are in training to become teachers. The purpose of our study was to answer the following questions:

1) What are prospective teachers' self-assessments about SEL beliefs, attitudes towards AI, and feelings about competence in using AI and SEL in teaching?
2) Are there any correlations between SEL beliefs and attitudes towards AI among prospective teachers?
3) What kind of different groups with homogeneous characteristics on synergy of beliefs about SEL and AI systems can be recognized among prospective teachers?

This study is part of the SETCOM project – Supportive Environments to Enhance Transversal Competencies in Education. The data was collected by a 1KA online survey among students at the University of Maribor, Slovenia. Graduate and postgraduate students enrolled in study programs for becoming class teachers, subject teachers, school counsellors and kindergarten teachers at the Faculty of Education, the Faculty of Arts, and the Faculty of Natural Sciences and Mathematics in the academic year 2022/2023 participated in this study. All students attended the SEL and AI educational modules implemented during the SETCOM project. This study used the data set of the first survey among participants before the educational intervention on SEL in AI in teaching (project Module B).

Methods

This study is based on the empirical quantitative methodological approach, using an online survey with closed-ended questions related to students' attitudes towards SEL and AI.

Measures

A standardised tool, the Teacher SEL Beliefs Scale, was used to measure teachers' attitudes towards social and emotional learning (Brackett et al., 2012). The original questionnaire includes 12 items placed in 3 dimensions of belief. Each dimension was measured by an individual subscale, including four items: 1) "Comfort with teaching SEL programs", 2) "Commitment to learning about SEL", and 3) "School culture supporting SEL". We added two items about knowing SEL in self-assessment of competence at developing SEL in students. All items were assessed with a 5-point Likert scale (1–Strongly disagree, 2–Disagree, 3–Neutral, 4–Agree, 5–Strongly agree). A mean score of all items was calculated to form an overall score for all three dimensions (comfort, commitment, and school culture).

The General Attitudes Toward Artificial Intelligence Scale (GAAIS) by Schepman & Rodway (2020) was used to measure student attitudes towards AI use in teaching. The scale has 20 statements regarding general attitudes towards AI, 12 measuring positive attitudes and 8 measuring negative attitudes. All score items marked positive or negative in general attitudes towards AI were assessed by a 5-point Likert scale (1–Strongly disagree, 2–Disagree, 3–Neutral, 4–Agree, 5–Strongly agree). The mean of the positive items was taken to form an overall score for the positive subscale, and the mean of the negative items was taken to form the negative subscale. The higher score on the positive subscale and the lower score on the negative subscale show a more positive general attitude towards AI. Schepman & Rodway (2020) proved the adequacy of the factor structure and divergent and convergent validity of the GAAIS tool.

In both scales, we calculate the overall mean score only for respondents with a 60 % or higher response rate on individual subscales. Thus, it resulted in some missing data that was the highest on the subscale of the Negative General Attitudes towards AI (N=19), followed by N=10 missing cases on all three subscales of the Teacher SEL Beliefs Scale (comfort, commitment, culture), and N=4 missing cases on the subscales of Positive General Attitudes towards AI. The SEL Beliefs Scale and GAAIS were tested for measurement reliability by Cronbach's alpha. The findings are presented in the Results section.

Sample

In this study, a purposive, non-random sample of 328 university students in the pedagogical study programs (e.g. kindergarten teaching, class teaching, music education, art education, school counselling, and subject teaching in mathematics, humanities, social and natural sciences) was carried out. Table 1 shows that most participants were female (80.2 %) and had completed a 4-year secondary vocational school or grammar school program (73.8 %). The average age of the sample was 21.55 years. This study includes only regular, full-time students with an average of six months of work experience in education. The findings of this study could be generalised to similar populations of prospective teachers.

Table 1
Study sample demographic characteristics

Characteristics	N	%
Student teachers	328	100
Gender		
Male	63	19.2
Female	263	80.2
Not defined	2	.6
Level of education		
I. Uncompleted primary school	0	0
II. Completed primary school	0	0
III. Lower vocational education (2 years)	0	0
IV. Secondary vocational education (3 years)	5	1.5
V. Grammar school, secondary technical/ professional education (4 years)	242	73.8
VI./1. Post-secondary professional education	15	4.6
VI./2. Specialization in post-secondary educational program, higher education professional programs	59	18.0
VII. Specialization in higher education professional programs, university programs (BSc, BA), professional master's degree	3	.9
VIII. Specialization in university program, MSc, PhD	4	1.2
	M	SD
Age	21.55	2.30
Teaching experience (years)	.53	1.87

Data analysis

Descriptive statistics were calculated for all interval and numerical variables using frequency and percentage distribution, along with mean and standard deviation. Before inferential statistical analysis, variables were also tested for normal distribution by calculating Skewness, Kurtosis and applying the Kolmogorov-Smirnov test ($p \leq 0{,}05$). The variables that did not meet normal distribution criteria were excluded from further statistical analysis. The Pearson correlation coefficient was used to determine initial relationships between SEL beliefs about and attitudes towards AI among student teachers. The *p*-value of ≤0.05 was considered statistically significant. The statistical analyses were conducted using SPSS 29.0 software (IBM SPSS, Chicago, IL, USA).

A hierarchical cluster analysis was implemented to identify different types of prospective teacher profiles on SEL beliefs about the use of AI systems in schools. “This process allowed identifying the number of clusters that maximizes differences between clusters or groups and minimizes within-group differences on the dependent variables” (Doron et al., 2014, p. 92). The final goal is to organize large quantities by forming homogeneous groups (internal cohesiveness) from the heterogeneous sample (external insulation) (Ferligoj, 1989; Doron et al., 2014). Different statistical methods of clustering were tested. Ward’s method gave the most precise solution with a Squared Euclidian distance measure. Before the cluster analysis was employed, all data were standardized, and the measured scores were transformed into standardized z-scores (M = 0, SD = 1) (Ferligoj, 1989). This process was necessary for the comparison between different measurement scales. A visual dendrogram was used to identify clusters with the maximum differences between groups and the highest homogeneity within each identified group. The final solution of three clusters was saved as a new variable and used in further analysis to define the characteristics of revealed groups of prospective teachers related to their synergy of SEL beliefs about and attitudes towards AI, self-assessed competencies related to using SEL and AI in teaching and protecting health and well-being in school children. The resulting clusters were labelled with descriptive names based on shared characteristics.

Results

Relationships between student teachers' beliefs about SEL and AI and their self-assessed competencies for teaching

The prospective teachers in our study feel more competent at developing SEL than at using AI in teaching. Moreover, although they agree on being familiar with AI (M = 3.3), they don't agree on being fully competent at using AI in teaching (M = 2.8). On the contrary, they agree more with being fully competent in developing the students' social-emotional competencies (M = 3.2). However, this agreement was outscored by their self-assessment of competence in protecting health and well-being in a classroom (M = 4.7) (Table 2).

Table 2
Descriptive statistics and Pearson's correlation coefficients for student teachers' self-assessment about knowing the terms and feeling of being competent in using AI and SEL in teaching

	M	SD	Skewness	Kurtosis	1 *(r)*	2 *(r)*	3 *(r)*	4 *(r)*
1. I am familiar with the term "artificial intelligence" (AI).	3.34	.84	-.444	.485				
2. I feel fully competent in the use of AI in teaching.	2.85	.91	-.067	-.140	.626**			
3. I am well familiar with the term "social-emotional competencies".	3.40	.82	-.479	.101	.101	.041		
4. I feel fully competent in developing social-emotional competencies in teaching.	3.20	.85	-.175	-.033	.190**	.203**	.671**	
5. I feel fully competent in protecting health and well-being.	4.69	1.86	-.103	-.601	.120**	.042	.077	.085

Note. 1–4: 1–strongly disagree … 5–strongly agree; 5: 1–simple tasks with the support of others … 8–complex tasks with numerous interrelated factors, suggesting new ideas and processes; $*p \leq .05$, $**p \leq .01$.

Pearson's correlation showed that familiarity with the term AI or SEL is strongly and positively significantly related to the students' perception of competence at using AI/SEL in teaching ($r > .60$). Students who feel fully competent in the use of AI also feel capable to develop social-emotional competencies in students

(r = .203). Moreover, familiarity with AI seems to be weak but still contributes significantly to students' self-perception of being competent at developing SEL and protecting health and well-being in the classroom (r > .12) (Table 2).

Table 3 presents descriptive statistics for the main dimensions of the Teacher SEL Beliefs Scale and the GAAIS scale among university student teachers. The dimension of "*Commitment to learning about SEL*" (represented by statements such as "*All teachers should receive training on how to teach social and emotional skills to students*." or "*I want to improve my ability to teach social and emotional skills to students.*") seems to be the dimension of SEL beliefs among students that elicits the most agreement (M = 4.12). Student teachers are also positive about their comfort with teaching SEL programs in the classroom (e.g., as measured by "*Taking care of my students' social and emotional needs comes naturally to me*.") (M = 3.66). The lowest agreement of students was related to the dimension of "School culture supporting SEL" (M = 3.41). However, it must be pointed out that measurement of this dimension resulted in non-normally distributed data (Kurtosis coefficient = 1.762) and low reliability (α = .368). Therefore, the item "School culture supporting SEL" was excluded from further data analysis.

The GAAIS was measured with two subscales, assessing positive and negative general attitudes towards AI. Although the prospective teachers generally showed positive attitudes towards AI (M = 3.48), at the same time, they expressed high scepticism about using AI in teaching (M = 3.23). The prospective teachers are particularly afraid that AI could be used for spying on people (M = 3.44), for taking control over people (M = 3.40), for causing danger (M = 3.37) and for unethical use by institutions (M = 3.32). The low standard deviations in all measured subscales showed relatively homogeneous student beliefs about SEL and AI.

A Cronbach alpha with coefficients between .73 and .87 showed the high internal consistency of the measurement tool for the four implemented subscales. One exception, the subscale "School culture supporting SEL" of the SEL Beliefs Scale was below reliable measure (α = .368) and therefore excluded from further data analysis (Table 3).

Table 3
Descriptive statistics for Teacher SEL Beliefs Scale and GAAIS

	N	M	SD	Skew-ness	Kurto-sis	α
Comfort with teaching SEL programs	318	3.66	.57	-.398	.273	.734
Commitment to learning about SEL	318	4.12	.68	-.517	-.196	.867
School culture supporting SEL	318	3.41	.48	-.154	1.762	.368
Positive general attitudes towards AI	324	3.48	.51	-.328	.945	.832
Negative general attitudes towards AI	309	3.23	.66	-.371	.492	.821

Table 4
Pearson's correlation between student teachers' attitudes towards SEL and AI and self-assessed competencies for using AI, developing SEL, and protecting health and well-being in teaching

	1 *(r)*	2 *(r)*	3 *(r)*	4 *(r)*	5 *(r)*	6 *(r)*
1. GAAIS – Positive General Attitudes Toward AI Scale						
2. GAAIS – Negative General Attitudes Toward AI Scale	-.337**					
3. I feel fully competent in the use of AI in teaching.	.312**	-.169**				
4. SEL Beliefs Scale – Comfort	-.065	.096	.021			
5. SEL Beliefs – Commitment	.016	.117*	-.213**	.350**		
6. I feel fully competent in developing social-emotional competences in teaching.	.042	-.005	.203**	.446**	.142*	
7. I feel fully competent in protecting health and well-being.	-.018	-.006	.019	.130*	.057	.086

Note. *$p \leq .05$; **$p \leq .01$

The Pearson's correlations in Table 4 show a statistically significant and strong positive correlation between students' SEL beliefs and the feeling of being competent at developing social-emotional competencies in teaching ($r \geq .35$). Students who feel comfort with SEL are also committed to learning about SEL ($r = 0.45$). Comfort with SEL is also the only belief that is significantly related to the feeling of being competent to protect the health and well-being of students ($r = .13$). On the contrary, negative attitudes towards AI are statistically significant and negatively related to the positive attitudes towards AI ($r = -.34$) and feeling competent to use AI in teaching ($r = -.17$). Students who have positive general attitudes towards AI also feel more competent at using AI in teaching ($r = .31$).

The Pearson's correlations between SEL and AI attitudes (Table 4) revealed a significant moderate positive correlation between feeling fully competent at using AI in teaching and feeling fully competent at developing SEL in teaching ($r = .20$), and a weak significant correlation between negative general attitudes towards AI and commitment to SEL ($r = .12$). Students who have stronger negative attitudes towards AI are more committed to learning about SEL. Conversely, feeling competent at using AI in teaching is statistically significant and negatively related to the students' commitment to learning about SEL ($r = -.21$).

Identifying prospective teachers' profiles on SEL beliefs about the use of AI in schools

Synergy of beliefs about SEL and AI in schools were analysed among prospective teachers by cluster analysis. The hierarchical cluster analysis with dendrogram revealed three distinct groups of students (Table 5). In the first group, named "SEL & AI advocates", were placed students with a very high commitment to learning about SEL ($M = 4.36$), a good comfort level with teaching SEL ($M = 3.81$), and positive general attitudes towards AI ($M = 3.86$). In the second group, named "SEL believers & AI sceptics", were placed students with high positive attitudes towards SEL, particularly in their commitment to learning about SEL ($M = 4.31$), and stronger negative attitudes towards AI ($M = 3.67$). The positive attitudes towards AI in the second group have the lowest mean among all three cluster groups, although it is generally still positive ($M = 3.25$). The third group, "SEL & AI sceptics", placed students with the lowest mean in all SEL beliefs and attitudes towards AI. Their commitment to learning about SEL ($M = 3.07$) is particularly low. All three groups of students expressed a high level of agreement with being competent to protect the health and well-being of students in a classroom (M > 4.5). However, we found differences in assessing competences related to SEL and AI in teaching. “SEL believers & AI sceptics” and “SEL & AI sceptics” feel less competent in AI than “SEL & AI advocates”, and “SEL & AI sceptics” feel the least capable of developing social-emotional competencies in students. Self-assessed competencies were highest among “SEL & AI advocates” in all subscales. The distinctions between the cluster groups are presented in Figure 1.

Table 5
Hierarchical cluster analysis solution and differences in group characteristics

	SEL Beliefs		General attitudes towards AI		Feeling competent			Cluster size	Hypothesized cluster name
	Comfort	Commitment	Positive	Negative	SEL	AI	Health		
	M (SD)	M (SD)	M (SD)	M (SD)	M (SD)	M (SD)	M (SD)	N (%)	
Group 1	3.81 (.59)	4.36 (.53)	3.86 (.38)	2.76 (.57)	3.38 (.87)	3.07 (.94)	4.94 (1.92)	107 (36.1)	SEL & AI advocates
Group 2	3.72 (.51)	4.31 (.48)	3.25 (.45)	3.67 (.46)	3.15 (.88)	2.67 (.88)	4.53 (1.88)	137 (46.3)	SEL believers, AI sceptics
Group 3	3.21 (.52)	3.07 (.34)	3.27 (.46)	3.11 (.45)	3.06 (.75)	2.90 (.72)	4.65 (1.81)	52 (17.6)	SEL & AI sceptics

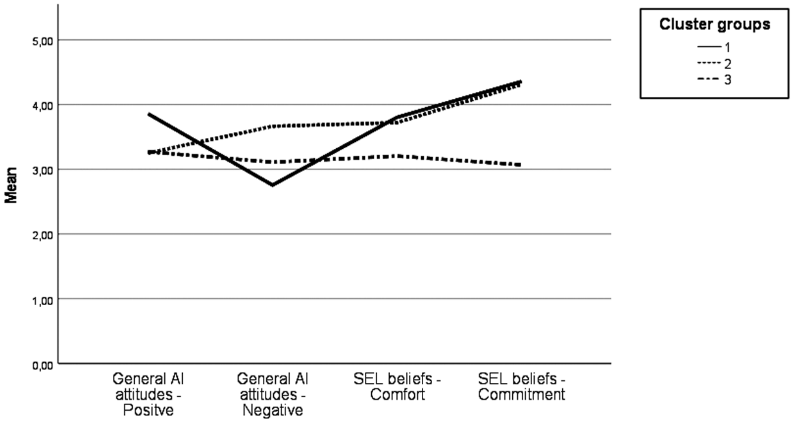

Figure 1
Three cluster groups of prospective teachers concerning their SEL beliefs and AI attitudes

Discussion

In this study, we were interested in the synergy between SEL beliefs about and attitudes towards AI in teaching from the perspective of university students – prospective teachers.

The findings showed that most teacher students in this study feel more competent in developing SEL than in using AI in teaching. However, familiarity with AI/SEL strongly predicted the students' perception of competence for using AI/SEL in teaching. However, our study yielded findings similar to those of Collie et al. (2015). In our study, the dimension of "*Commitment to learning about SEL*" was the dimension of SEL beliefs that elicited the most agreement among students, followed by the dimension of "Comfort with teaching SEL programs", while the dimension eliciting the least agreement was "School culture supporting SEL". Based on the defined SEL groups of teachers by Collie et al. (2015), in our sample, we recognised "SEL advocates" as those who were highly committed to learn about SEL but had lower levels of belief about SEL and insufficient support for it in the school environment.

Insufficiently critical attitudes towards AI can lead to people choosing convenience over privacy. Teachers are not exceptions in this, and they could accept the immediate benefits of AI while failing to question its impact and or ask why (e.g., For whom was this done? What am I unwittingly giving up when I use these technologies? How much is it worth?) (Luckin et al., 2022). There is a significant risk in assuming that computers always get things right. Belief in so-called “technochauvinism”, the notion that technology is always the solution, has led to a proliferation of poorly designed systems (Broussard, 2019). Following Broussard’s (2019) idea, it is crucial to teach prospective teachers that all social problems cannot be solved through digitally enabled systems and that technology, like humans, has limitations. Developing critical attitudes towards AI seems to be one of the most important and challenging areas of synergy between AI and SEL. SEL can significantly contribute to a challenging examination of young people’s relationship with AI and a more thoughtful approach to AI integration into human lives. Based on the findings of our study, “SEL believers & AI sceptics” are much more sceptical and critical towards the use of AI in teaching in comparison with the other two identified cluster groups, “SEL & AI advocates” and “SEL & AI sceptics”. These findings are significant for understanding that commitment to learning about SEL is related to critical attitudes towards AI and the feeling of being competent to use AI in teaching.

However, findings from the correlational analysis revealed that students who feel competent to use AI in teaching also feel competent to develop SEL in teaching. With this in mind, our findings showed that integrating the development of SEL and AI as transversal competencies into everyday teaching is essential. Transversal competencies should be promoted and encouraged at all educational levels and in all subjects. Moreover, we agree with Bartlett (2019) that SEL and the use of AI should primarily be taught in health education, whose curriculum is directly linked to promoting and enhancing school children’s physical and mental health. The focus in teaching SEL and AI should be on skill development (i.e., what students can do) and less on cognitive learning (i.e., what students can know). Future studies should investigate the correlation between SEL beliefs about and attitudes towards AI among school teachers. Also, the impact of social-demographic factors, such as gender, working experience in teaching, educational level, and previous education on SEL/AI should be considered, as well as other factors, such as the level of stress related to AI and SEL, school support and the curriculum.

Finally, some methodological limitations of this study should be taken into consideration. Despite the high reliability of the measurement scales used here, it should be emphasized that the subscale of “School culture supporting SEL” on the SEL Beliefs Scale (Brackett et al., 2012) showed a low Cronbach alpha coefficient and resulted in unreliable measures in this study. The study limitation of the subscale “School culture supporting SEL” could predict that statements in this dimension were related to teachers’ experiences in the school environment, accessible only to teachers employed at schools. Student teachers in this study have only an average of six months of work experience in teaching. From this point of view, they could be much less experienced and familiar with SEL implementation and SEL support from school management. Therefore, the subscale “school culture” should be transformed and adjusted to the experiences of the prospective teacher population in future studies. This is because this domain on the SEL Beliefs Scale was shown to be among the most influential factors in teachers’ experience of stress and may play an even more critical role than their own beliefs about SEL (Collie et al., 2015).

Conclusions

The current study identified three profiles among SEL and AI beliefs of prospective teachers. The cluster typology indicated two opposite sides of the synergy spectrum: the group of “SEL & AI advocates” and the group of “SEL & AI sceptics”. At the same time, most students from the pedagogical study programs were placed in the group of SEL believers & AI sceptics. Importantly, this study indicated statistically significant correlations between SEL and AI beliefs, showing that SEL can significantly contribute to critical thinking towards the use of AI in school. SEL and AI as transversal competencies should be strategically developed in the university education of prospective teachers to improve their comfort with SEL and positive attitudes towards AI in teaching. Future studies are needed to address prospective teachers’ beliefs about supporting SEL and AI in their education.

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Differences in Perception of Social and Emotional Learning among Teachers Working at Different Educational Levels

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Abstract

Teachers' perceptions of social and emotional learning (SEL) are essential because the implementation, evaluation, and outcome of SEL programs depend heavily on them. The aim of the article is to examine various aspects of SEL among teachers in relation to the level at which they teach. Specifically, we examined the three scales pertaining to teachers' comfort with teaching SEL, commitment to learning about and teaching SEL, perceptions about whether the school culture supports the SEL program and added perceptions of the importance of SEL in general. Our final sample consisted of 185 educators working at different educational levels, i.e., as kindergarten teachers, primary school teachers, high school teachers, or higher education teachers. All groups of teachers perceived SEL as important and felt comfortable with delivering SEL instructions but differed significantly in their commitment to learning about and teaching SEL and their perception of how much the school culture supported SEL. Further research is needed to understand SEL implementation by exploring the beliefs that underpin it at different levels of education and the need for tailored professional development in delivering SEL instruction.

Key Words: education, social and emotional learning, teachers' perceptions, levels of education

Introduction

The importance of social and emotional learning in the society of the future

Social and emotional competencies (SEC) are increasingly recognised as important competencies for individuals in the society of the future (Council of the European Union, 2018), which is becoming more and more optimized and dependent on artificial intelligence (AI) (OECD, 2021a). Although it seems that solutions for today's problems should be found solely in the latest technology, research shows that for sustainable progress, we need both effective technology and admirable people. The World Economic Forum (WEF, 2017) has recognised factors that can increase organisational chances of success. Organisational effectiveness, leadership skills, problem solving, goal orientation, reliability, responsibility, collaboration, and teamwork are all needed, along with the will to develop further. *The Future of Jobs Report* (2023) lists the most desirable business skills as curiosity, lifelong learning, resilience, flexibility, agility, motivation, and self-awareness. Moreover, it states that SEC learning hours have steadily increased from 2017 to 2023, especially in promoting creativity, self-initiative, and ethics (pp. 44–45). SEC help individuals to understand and regulate their own emotions, communicate effectively, build positive relationships, cope with stress, and increase employee productivity (Babatunde et al., 2023). Research proves cognitive, social, and emotional skills improve life outcomes at an individual and a societal level, but we lack information on the development and importance of SEC compared to cognitive skills (OECD, 2021b). SEL significantly shapes an individual's success at work and improves the establishment and maintenance of positive interpersonal relationships, mental health, and employee well-being. Addressing this last issue results in fewer resignations and sickness absences, fewer accidents at work, improved productivity, and increased commitment to work (Žibret, 2018; Belfield et al., 2015). The same applies to teachers, who are the main promotors of the implementation, evaluation, and outcomes of SEL programmes (Chetty et al., 2014; Vršnik Perše et al., 2020). SEL plays an important role in lowering teacher burnout, reducing absenteeism and the process of leaving the teaching profession (Skaalvik and Skaalvik, 2011), and has an impact on teachers' personal development, success, and job satisfaction (Weiss, 2002; Collie, 2017). Teachers who experience greater satisfaction exhibit higher work enthusiasm and motivation, which has a significant impact on their teaching, and which further influences students' motivation and learning (Burić and Moè, 2020). Even more important is the teachers' role modelling of SEC and the inclusion of SEC in the school culture and climate (Nielsen et al., 2019).

Educational institutions are places, where young people can learn and sharpen these skills and are thus important locations for implementing SEL among students[1]. Unfortunately, empirical research (OECD, 2021b) shows that the levels of SEC among students are significantly too low. At a time of huge global changes in society, teachers[2] are required to have a high level of psychological flexibility and interpersonal sensitivity to meet the different needs of the students in their classes.

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[1] We use the term "student" as a superordinate for the words: child, pupil, high school student and university student.
[2] The term "teacher" is used as a superordinate for the words: teacher, professor, college teacher.

Social and emotional learning in education

SEL is an integral part of human development, takes place at all times, and is a lifelong process that is mostly implemented in an unsystematic and unintentional manner and is most effective in the context of supportive relationships (Košir, 2013). There are many different models, designed to promote the development of intra- and inter-personal competencies in a school setting (Berg et al., 2017). SEL components as defined by the Collaborative for Academic, Social, and Emotional Learning (CASEL) are self-awareness, self-management, social awareness, relational skills, and responsible decision-making (Weissberg et. al., 2015). They refer to the process of developing SEC to foster emotional well-being, healthy relationships, and effective decision-making of an individual through the acquisition and practical application of attitudes, skills, and knowledge (Reyes et al., 2012).

Multiple authors have examined the benefits of SEL for students' mental health and capacity to cope with stress (Achor, 2010), their positive perceptions of self and others (Durlak et al., 2011), positive peer relationships (Taylor et al., 2017), academic achievement (Bakračevič and Licardo, 2010; Durlak et al., 2011; Schonfeld et al., 2014), and its positive role as a protective factor for children at risk (Malti, 2020). (Meta)studies to date on SEL in school contexts largely confirm the positive effects of SEL at all levels of schooling (Durlak et al., 2011; Taylor et al., 2017; Mahoney et al., 2018), and three important school areas can be highlighted in which SEC has a significant impact on student's attitudes towards school, behaviour in school and their academic achievement (Zins et al., 2004).

Although the literature strongly supports SEL in general, programmes vary widely in the type of training, technical assistance, and support implementation (Shriver and Weissberg, 2020); some emphasise the explicit teaching of skills, while others attempt to link SEL to curricula, teaching practices and/or strategies to improve the school climate. Brackett et al. (2012) found that many teachers are motivated to integrate SEL into their work and, that teachers' implementation and the results of the SEL programme are invariably influenced by their beliefs about the SEL programme. In other words, teachers' beliefs are key indicators of their perceptions and consequently influence their teaching practice. Research is now increasingly focusing on how and under what conditions SEL has the greatest impact (Jones et al., 2019). Accordingly, five aspects have been specifically highlighted: quantity of programme delivery; adherence – components delivered as planned; quality of delivery – competence in delivery; responsiveness of participants – engagement; and programme differentiation – critical features that differentiate the programme (Durlak, 2016).

Teachers and SEL programmes: beliefs, knowledge, and practices

Teachers' beliefs play an important role in their work and are closely intertwined with their pedagogical practice and experience. They represent a filter for receiving, shaping, and interpreting information in the school field and guide teachers' intentions and actions (Fives and Buehl, 2012). Many authors have studied teachers' beliefs about self-efficacy, school climate, stress, and other issues (Burić and Moè, 2020; Ransford et al., 2009). In the present study, we were especially interested in teachers' beliefs about SEL. Positive beliefs about SEL are associated with greater confidence in SEL implementation, openness to SEL programmes, perceived programme effectiveness, implementation of SEL content in informal learning, reduced incidence of burnout, and increased beliefs about overall self-efficacy in teaching (Brackett et al. 2012; Ransford et al., 2009).

There are also many measurements that evaluate teachers' SEL attitudes, knowledge, and practices (Medina, 2023, Brackett et al., 2012). We focused on the SEL Teachers' Beliefs scale by Brackett et al. (2012), a 12-item scale that assesses the following: a) teachers' *comfort* with delivering SEL instructions – they have the skills and knowledge and are confident about teaching SEL; b) *commitment* to learning about and teaching SEL – beliefs that holistic development of students is important, and c) perception of supportiveness of their *school's culture* for SEL **–** practicing SEL in an environment that supports, enables, and encourages SEL. We added 4 additional questions to measure teachers' perceptions about SEL in general. However, beliefs may vary depending on individual and organizational factors, with the last one supporting training and the experience teachers have with SEL (Collie et al., 2011). SEL comfort and SEL commitment address teachers' individual beliefs, whereas SEL culture deals with teachers' perceptions of the organizational culture. Teachers who express serious support for SEL may have a more positive view of SEL than teachers where this is not the case (Collie et al., 2015).

Comfort with delivering SEL

Teachers' comfort in delivering SEL programmes in classes consists mostly of teacher confidence in implementing the programme correctly and managing the classroom during lessons. Teachers are more likely to continue using a program when they feel comfortable with and enthusiastic about it (Brackett et al., 2012).

Commitment to learning and teaching SEL

Teachers' commitment refers to the existence of a transfer between the person and an object to which he or she is committed. Besides professional "subject" development, it also assumes involvement in SEL programmes. It is the commitment to continuous professional development in SEL by all stakeholders, including the endorsement of a shared vision by school staff and leadership to ensure success (Brackett et al., 2009). Commitment to learning and teaching SEL foresees the ability to implement SEL programmes and model the skills that these programmes foster in children. We can distinguish between professional and organizational commitment; the first refers to the teaching profession in general and the second to individual identification with and involvement in the concrete organisation where he or she works. These factors influence teachers to work differently. Collie and colleagues (2011) explored the relationship between teacher and student and a positive and cooperative classroom environment and found that differences in the teacher's level of comfort and perceived support for SEL, alongside a lack of commitment to SEL, are associated with teacher stress or satisfaction, and do have an impact on teaching effectiveness and student outcomes.

School culture supporting SEL

Leadership by school directors has a strong impact on the adoption of the programme, its implementation, and the longevity of sustained implementation. In fact, the effects of SEL on students are strongest when high levels of principal support and teacher quality of SEL implementation interact (Ransford et al., 2009).

Research problem and hypotheses

As we can see in the theoretical part, much research highlights the importance of introducing SEL in today's educational institutions at all levels of education. In this study, we sought to investigate differences among teachers at various educational levels (kindergarten, primary school, high school, and higher education) in their attitudes toward SEL, especially focusing on three key subscales: comfort with delivering SEL instruction, commitment to learning about and teaching SEL, and perceptions of how school culture supports SEL. We were interested in whether we could find distinct patterns of those three subscales among teachers at different educational levels. We were also interested in teachers' perceptions of the importance of implementing SEL in general.

We posed four hypotheses:

Hypothesis 1: Teachers at different levels of education differ in their comfort with delivering SEL instruction.

Hypothesis 2: Teachers at different levels of education differ in their commitment to learning about and teaching SEL.

Hypothesis 3: Teachers at different levels of education differ in their perception of how much the school's culture supports SEL learning.

Hypothesis 4: Teachers at different levels of education differ in their understanding and perception of the importance of SEL.

Method

Our final sample consisted of 185 individuals working in education. Most of the participants were female (80 %), with an average age of 45.31 years (SD = 10.39). Teachers at different levels of education are represented in our sample: 19.5 % worked as kindergarten teachers, 29.7 % were primary school teachers, 25.9 % were high school teachers, and 24.9 % worked in higher education. Most of the participants had a master's degree (43.8 %), followed by participants with a Ph.D. (24.3 %) or a bachelor's degree (16.2 %). The average work tenure of the sample was 20.21 years (SD = 10.68).

After the teachers had participated in an educational module on the topic of AI and SEL, we administered an anonymous online survey. To measure their attitudes towards SEL, we used a Slovene translation of the Teachers' Beliefs About Social and Emotional Learning Scale (Brackett et al., 2012). The scale is comprised of three subscales. It uses four items to measure comfort with delivering SEL instruction (sample item: "I feel confident in my ability to provide instruction on social and emotional learning"; α = .84); four items to measure commitment to learning about and teaching SEL (sample item: "I would like to attend a workshop to learn how to develop my students' social and emotional skills"; α = .91), and four items to address participant's perception of how much the school's culture supports SEL learning (sample item: "The culture in my school supports the development of children's social and emotional skills"; α = .75). In addition to the established subscales, we developed three items to address teachers' level of understanding and their perception of the importance of SEL (sample item: "Social and emotional learning is of great importance in school and educational contexts."; α = .86).

To test our hypotheses, we first examined the distribution of the variables of interest. Considering that neither variable was normally distributed, we proceeded with the nonparametric Kruskal-Wallis test to examine our hypotheses.

Results

Means, standard deviations, and correlations between the dimensions of teacher's beliefs about SEL can be found in Table 1.

Table 1
Descriptive statistics and correlations between variables

	N	M	SD	1	2	3	4
1. Comfort	173	3.83	0.62				
2. Commitment	173	3.92	0.73	.314**			
3. Culture	173	3.72	0.56	.339**	.274**		
4. Understanding & importance	172	4.01	0.56	.364**	.597**	.243**	

***p < .001, **p < .01; *p < .05

Table 2 shows the results of hypotheses examination. According to the Kruskal-Wallis test, the four groups of teachers differ significantly in their commitment to learning about and teaching SEL and their perception of how much the school's culture supports SEL. However, no significant differences in teacher's comfort with delivering SEL instruction or their level of understanding and perception of the importance of SEL were observed. In other words, the result lends support for Hypotheses 2 and 3, but not for Hypotheses 1 or 4.

Table 2
Results of the Kruskal-Wallis test

		N	Mean Rank	H (3)	p
Comfort	Kindergarten teachers	34	96.93	2.99	.394
	Primary school teachers	53	89.98		
	High school teachers	46	83.27		
	Higher education teachers	40	78.90		
Commitment	Kindergarten teachers	34	87.21	8.69	.034
	Primary school teachers	53	93.14		
	High school teachers	46	69.79		
	Higher education teachers	40	98.48		
Culture	Kindergarten teachers	34	81.40	12.67	.005
	Primary school teachers	53	92.83		
	High school teachers	46	101.98		
	Higher education teachers	40	66.81		
Understanding & importance	Kindergarten teachers	33	92.35	4.75	.191
	Primary school teachers	53	89.60		
	High school teachers	46	73.27		
	Higher education teachers	40	92.78		

To gain further insight into any significant differences, we carried out post-hoc pairwise comparisons. Results for teachers' commitment to learning about and teaching SEL can be found in Table 3, revealing that high school teachers, who obtained the lowest average rank (see Table 2), were significantly lower than primary school and higher education teachers. However, their commitment to learning about and teaching SEL was not significantly lower than the commitment of kindergarten teachers, who obtained the second lowest rank.

Table 3
Pairwise comparisons for Commitment

		MD	SE	p
Kindergarten teachers	Primary school teachers	-0.14	0.16	.807
	High school teachers	0.30	0.18	.369
	Higher education teachers	-0.19	0.16	.655
Primary school teachers	Kindergarten teachers	0.14	0.16	.807
	High school teachers	0.44	0.15	.021
	Higher education teachers	-0.05	0.12	.978
High school teachers	Kindergarten teachers	-0.30	0.18	.369
	Primary school teachers	-0.44	0.15	.021
	Higher education teachers	-0.49	0.16	.012

Note. MD = Mean difference. SE = Standard error.

Lastly, we examined differences between groups for teachers' perception of how much the school's culture supports SEL learning; results can be found in Table 4. Combining the results of pairwise comparisons (see Table 4) with mean ranks for different groups of teachers (see Table 3), we can see that higher education teachers have the lowest confidence in a culture that supports SEL learning, significantly lower than primary and high school teachers. However, they are not significantly different from kindergarten teachers, who obtained the second-lowest average rank.

Table 4
Pairwise comparisons for Culture

		MD	SE	p
Kindergarten teachers	Primary school teachers	-0.17	0.11	.399
	High school teachers	-0.23	0.14	.321
	Higher education teachers	0.14	0.13	.716
Primary school teachers	Kindergarten teachers	0.17	0.11	.399
	High school teachers	-0.06	0.11	.954
	Higher education teachers	0.31	0.11	.021
High school teachers	Kindergarten teachers	0.23	0.14	.321
	Primary school teachers	0.06	0.11	.954
	Higher education teachers	0.37	0.13	.030

Note. MD = Mean difference. SE = Standard error.

Discussion

The goal of this research was to assess teachers' beliefs about SEL. In our research, one primary finding emerged: teachers' perceptions about SEL vary according to the level at which they teach.

Supporting SEL in schools involves helping students and teachers develop skills to understand and manage emotions, set positive goals, show empathy, build strong relationships, and make responsible decisions (Weissberg et. al., 2015). Effective implementation of SEL programs often results in better academic achievements, improved teacher-student relationships, and a reduction in problematic behaviours (Durlak et al., 2011; Owens et al., 2014). This underscores the importance of identifying and measuring the factors influencing the success of SEL programming. Brackett et al. (2012) present a valuable framework for understanding teachers' perceptions of SEL, which is recognized as a critical component of modern education. In addition to the three established subscales for measuring teachers' perceptions of SEL—i.e., comfort (sense of confidence in teaching SEL), commitment (desire to participate in SEL training and teaching), and culture (schoolwide support for SEL)—three questions to address teachers' level of understanding and perception of the importance of SEL in general were added.

In the study by Brackett et al. (2012) only teachers from kindergarten to the end of primary school (8th grade) were included. Miller et al. (2023) later expanded the research to 12th grade teachers (high school) and into a non-Catholic district. Besides kindergarten, primary school, and high school teachers, we additionally examined teachers in higher education. Women dominated in all these studies—Miller et al. (2023; 81 %), Brackett et al. (2012; 90 %)—which is to be expected as they are more often employed in lower levels of education (in Slovenia in the school year 2022/23, the percentage of women teachers in kindergarten was 97.3 %; in primary school, 88.3 %; in high school, 67 %; and in higher education the ratio changes to 45.1 %; SURS, 2023).

In accordance with previous research (Buchanan et al., 2009), all teachers in our study, regardless of their level of teaching, understood and perceived SEL as an important part of school and educational contexts (kindergarten teachers, p=92.35; primary school teachers, p= 89.60; high school teachers, p=73.27, and higher education teachers, p=92.78).

Examining the dimensions of SEL more closely, our study yields different patterns of response among teachers from different levels of the education system. High school teachers, on average, exhibit a lower level of commitment to SEL compared to primary school and higher education teachers, but not significantly lower than that of kindergarten teachers. The lower commitment to SEL instruction among high school teachers can be attributed to several factors. The differences in commitment to learning about SEL among high school, primary school, and higher education teachers can be attributed to a combination of student developmental stages, academic priorities, teacher training, time constraints because of curriculum demands, external pressures, and standardised pedagogical practices. High school students are at different developmental stages compared to primary school and higher education students. They are in adolescence, a stage marked by significant emotional and social changes. Teaching and supporting them can be more challenging and demanding. High school teachers may believe that SEL is more relevant in earlier grades when foundational emotional and social skills are being formed. They may perceive SEL as less directly relevant to their curriculum. This viewpoint is supported by the need to cover specific subject matter to prepare students for college or other post-secondary pathways. Teachers may feel pressured to prioritize academic content over SEL, as they believe this is what their students need to succeed on standardized tests. High schools may face external pressures related to standardized testing and accountability measures that prioritize academic achievement. This perception could lead to a lower commitment to SEL instruction than to a fixed schedule with limited flexibility. High school teachers may perceive a lack of time to incorporate SEL activities into their curriculum, especially when compared to primary school teachers, who often have more flexibility in their daily routines. Primary school teachers may also receive more specialized training in child development, including SEL, as part of their teacher preparation programs. In contrast, high school teachers may have received less training in SEL, which could affect their commitment to implementing SEL practices effectively. Further research is needed to clarify this issue.

Our study also indicates that higher education teachers perceive the lowest levels of school culture supportive of SEL, significantly lower than primary and high school teachers, but not significantly different from kindergarten teachers, who obtained the second lowest average rank. Lower culture scores and less supportive working environments in schools lead to greater emotional exhaustion among teachers (Halbesleben, 2006). The disparities in teacher perceptions can be attributed to various factors. Higher education teachers may perceive a lower level of institutional support for SEL because of the emphasis on academic and professional development, on lecturing, research, and academic mentoring, rather than on providing social and emotional support. The primary focus is often on subject matter expertise, research, and career preparation. As a result, the academic culture in higher education may place less emphasis on the holistic development of students, including their social and emotional well-being, compared to primary and high school levels, where students may require more guidance and support. A shortage of institutional support for SEL may exist because of the autonomy of higher education students, the absence of formal SEL programs, and traditional role expectations within higher education institutions. Many higher education institutions do not have formalized SEL programs or initiatives integrated into their curricula. This absence of structured SEL programs can contribute to the perception among higher education teachers that SEL is not a significant aspect of the institution's culture or mission. Higher education institutions may be influenced by external factors such as accreditation standards and funding priorities. These external pressures often prioritize academic outcomes, research productivity, and career readiness over SEL initiatives. This can thus create the perception that SEL is not a top institutional priority.

We were surprised by the results of the survey regarding kindergarten teachers' commitment to SEL and their low perceptions of kindergarten culture regarding SEL. Kindergarten teachers and principals may have misconceptions about the appropriate age for teaching SEL, with some believing that these skills are better suited for older students. However, the development of social and emotional skills in early childhood is important as it lays the foundation for success in school and life. Kindergarten teachers also typically receive training in early childhood development that may not emphasize SEL to the same extent as primary school teachers who specialize in elementary education. The emphasis in kindergartens is often on basic caregiving tasks and preparing children for the school environment, which can reduce the time and attention that teachers dedicate to SEL. The focus in kindergartens often centres on family support and a safe environment rather than on SEL.

This research highlights the importance of acknowledging and addressing diverse perspectives on SEL; and individual-level factors like beliefs (Miller et al., 2023) and contributes to a more comprehensive understanding of SEL by exploring the perceptions that underpin them at different levels of education.

Conclusions

Our findings highlight the complexity of implementing SEL in education and emphasize the importance of acknowledging and addressing the unique perceptions held by teachers at different educational levels. Although the sample of Slovenian teachers included in the study was evenly distributed according to the level of education, it was relatively small and consisted mainly of women, which limits the generalizability of our findings, we believe that the study provides valuable insights into teachers' beliefs about SEL.

In future studies, it would be useful to survey a larger sample of teachers from different countries and cultural contexts, working at all levels of education, to explore the impact of gender differences on perceptions about SEL.

Furthermore, the need for tailored professional development to enhance educators' confidence, competence, and commitment in delivering SEL instruction is emphasized, especially for high school and kindergarten teachers, and to empower school principals and teachers, with a focus on higher education and kindergarten teachers, so that time spent on creating an appropriate classroom or school climate is not time wasted. Only when teachers and principals create a classroom or school climate in which students feel included, SEC can be developed and expanded by students.

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Teachers' Attitudes about Social and Emotional Learning as Predictors of their Relational Competence

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Abstract

This study investigates teachers' attitudes toward social and emotional learning (SEL) as predictors of different dimensions of their relational competence. With a sample of educators from different stages in the educational system, our study finds that the two most consistent predictors of positive teacher relational outcomes were teachers' comfort with supporting social and emotional learning and their commitment to learning about and enhancing social and emotional learning. These findings suggest that teachers who are confident in their abilities to enhance students social and emotional competencies and are committed to ongoing trainings and learning related to enhance them are more likely to develop and maintain positive relationships with students. Surprisingly, perceived school culture support for SEL and understanding its importance were not significant predictors. The study suggests that enhancing teachers' SEL-related self-efficacy could further develop their relational competence. Limitations include the cross-sectional design and reliance on self-reported measures. The findings of our study highlight the need for professional development focused on SEL within teacher training programs.

Key words: social and emotional learning, teachers, beliefs, relational competence

Introduction

The primary aim of education, as defined in normative acts within the realm of educational legislation in Slovenia, is to facilitate the comprehensive development of children and adolescents. This entails not only the provision of guidance in achieving academic objectives but also a systematic cultivation of students' capacity to navigate a spectrum of emotions, regulate behaviour, engage in respectful communication, and effectively manage conflict. This process, called social and emotional learning, should not be left to a hidden curriculum; instead, it needs to be systematically and procedurally integrated into the educational process. However, evidence drawn from research and school reports indicates that this crucial dimension has been marginalized in Slovenian schools.

Teachers are the primary implementers that can systematically raise students' social and emotional competencies. A prerequisite for systematically supporting the social and emotional learning of children and adolescents in educational contexts is teachers' willingness to continuously reflect on their own practice, i.e., readiness to engage in their own social and emotional learning and build their relational competence. Their beliefs about social and emotional learning and their own role in enhancing it are likely to influence their teaching and classroom management as well as their relational competence. Therefore, the aim of the present study was to investigate teachers' beliefs about social and emotional learning as predictors of their relational competence. Teachers from the entire education vertical, from kindergarten to higher education, were included in the sample.

Social and emotional learning in educational context

Educational institutions are, alongside the family, a key context for individual learning and development – a place where children and young people learn about themselves and others, and about the values and expectations of the community. The kindergarten, school or university environment significantly shapes the social and learning behaviour of children and adolescents and, considering their developmental needs, supports constructive patterns of beliefs and behaviour or, if unfavourable, contributes to the development of unproductive patterns of belief and behaviour. Educational institutions are therefore an important context not only for cognitive learning (learning subject knowledge and skills), but also for social and emotional learning. Social and emotional learning is the process through which people learn about themselves and others; it takes place all the time, largely unsystematically and unintentionally (following the principles of the hidden curriculum).

Social and emotional learning in the broadest sense of the word is therefore happening all the time in educational institutions, even in a non-systematic, non-targeted and unintentional way. In the narrower sense of the word, social and emotional learning is defined as a process that builds students' skills in recognizing and managing their emotions, appreciating the perspectives of others, establishing positive goals, making responsible decisions, and handling interpersonal situations through developmentally and culturally appropriate classroom instruction and application of learning in everyday situations (Greenberg et al., 2003). Thus, social and emotional learning provides a framework for various domains, such as training social competence, preventing bullying and violence, mental health promotion, and enhancing positive youth development, offering the explanation that intrapersonal, interpersonal and cognitive skills can be developed (Gueldner et al., 2020). The emphasis on learning communicates that these developmental skills can be taught through instruction, practice and feedback. Thus, these competencies should be incorporated into curricula and systematically developed through instructional activities.

Research shows that fostering social and emotional learning not only improves achievement, but also increases prosocial behaviours, improves student attitudes toward school, and reduces depression and stress among students (see e.g., Durlak et al., 2011). One of the established models that conceptualize social and emotional competencies is CASEL (Collaborative for Academic, Social, and Emotional Learning; see Bridgeland et al., 2013; DePaoli et al., 2017; Ross & Tolan, 2018; Schonert-Reichl et al. 2017). The CASEL model of social and emotional learning is a comprehensive framework designed to promote the development of essential life skills in individuals. It emphasizes five core competencies: self-awareness, self-management, social awareness, relationship skills, and responsible decision-making. By addressing these competencies through structured educational approaches, the CASEL model aims to enhance students' interpersonal skills, and overall well-being. Another useful framework for conceptualizing social and emotional competencies in curricula is provided by The European Framework for Personal, Social and Learning to Learn Key Competence (LifeComp) (Sala et al., 2020). This is a conceptual, non-prescriptive framework for establishing a shared understanding and a common language on the personal, social and learning to learn key competencies and can be used as a basis for the development of curricula and learning activities.

Most school curricula, including Slovenian curricula for kindergarten, elementary school and upper-secondary school, include social and emotional competencies as common or transversal objectives, or as competencies that need to be thoughtfully and systematically integrated into the curriculum, both at the level of subject-related content and skills (where possible) and through general didactic and educational/psychosocial recommendations for all teachers. The pursuit of such objectives, unlike many cognitive objectives, cannot be assessed through knowledge tests, thereby problematizing any assessment of the extent to which our educational system contributes to achieving outcomes related to social and emotional learning. This challenge arises because the attainment of these outcomes is not systematically evaluated, despite the legal provision that the evaluation of the implementation of educational plans should ideally be conducted annually. As a result, it can be reasonably assumed that the potential for intentional, systematic, and reflective efforts to support students' social and emotional learning in educational institutions is underutilized.

International research studies, which, besides measuring academic outcomes, provide insight into the achievement of social and emotional outcomes, can serve as a valuable source of data regarding the viewpoints of various stakeholders in education (students, teachers, principals, and sometimes parents). The results of recent international assessments such as TIMSS (2015) and PIRLS (2016) indicate that the achievements of fourth-grade students in reading, mathematics, and science literacy, as well as the achievements of eighth-grade students in mathematics and science literacy, are favourable in comparison to the international average. However, Slovenian fourth-grade students rank poorly compared to their peers in other countries in terms of self-reported school belongingness, and eighth-grade students even rank last in this regard (Mullis et al., 2016; Mullis et al., 2017). These tendencies are indirectly supported by the results of the latest PISA study (Šterman Ivančič, 2019), which showed that Slovenian adolescents' achievements in reading, mathematics, and science literacy are good compared to the international average. Nevertheless, our students reported lower teacher support, perceived teacher engagement, and frequency of feedback from teachers compared to students in other OECD countries. Slovenian students also reported the lowest frequency of experiencing positive emotions, particularly pride and joy, compared to their peers from other countries.

It is thus very likely that a significant amount of social and emotional learning occurs implicitly and unsystematically, often manifesting in the form of a hidden curriculum (i.e., the unwritten, unofficial, and often unintended lessons, values, and perspectives that students learn in school, see Giroux & Penna, 1983). This implies that the potential positive influence that teachers could have on the social and emotional development of children and adolescents, by fostering positive patterns of self-awareness, relational competence, problem-solving, and responsible decision-making, is underutilized. Many negative cognitive and behavioural patterns (such as inappropriate attributions or dysfunctional self-perceptions of failure or abilities, peer exclusion, bullying, non-functional conflict resolution strategies, and other unfavourable aspects of classroom climate) can be prevented or reduced through deliberate educational interventions targeting students' social and emotional learning.

Teachers' supportive behaviour towards students, active monitoring, and willingness to engage in peer dynamics also constitute important factors influencing classroom behaviour and students' learning engagement. For instance, Shin and Ryan (2017) found that in classrooms with low levels of teacher emotional support, students are more prone to imitate disruptive behaviours displayed by their peers throughout the school year, leading to sustained higher levels of disruptive behaviour on the classroom level. Furthermore, Vollet et al. (2017) determined that during the transition to adolescence, a decrease in academic engagement is more pronounced among students perceiving lower teacher support, and that among adolescents with diminished teacher support, peer groups play a more significant role in influencing academic engagement. Additional justification for the necessity of more systematic support for social and emotional learning through the creation of secure and encouraging school environments is provided by contemporary scientific findings, indicating that individual development is shaped by the interplay of genetic or biological characteristics, relationships, as well as cultural and contextual factors (see Cantor et al., 2018; Osher et al., 2018). Furthermore, the lack of resources for developmental-preventive interventions in schools also has economic consequences (Belfield et al., 2015).

Teachers' relational competence as a prerequisite for supporting social and emotional learning

To systematically enhance students' social and emotional learning, teachers should be ready to engage in continuous self-reflection on their own practices, thus being motivated to engage in their own process of social and emotional learning. Teachers' relational competence is crucial not only for the development of social and emotional competencies in students (Schonert-Reichl, Roeser et al., 2015), but also for students' learning and development in general (Jennings & Greenberg, 2009; Jones et al., 2013).

The concept of teachers' relational competence can be situated within the broader context of teachers' social and emotional competence. The common characteristics of various definitions of relational competence is teachers' ability to establish and maintain positive, supportive and encouraging relationships with students. Juul and Jensen (2010) define teachers' relational competence as the ability to see a student as a unique being and to consequently adapt their own behaviour without abandoning the leadership role and their authenticity, while still taking full responsibility for the teacher-student relationship. Based on this model, Vidmar and Kerman (2016) proposed three main components of teachers' relational competence: (1) respect for individuality; (2) authenticity, and (3) responsibility for the relationship. The respect for individuality includes teacher's ability to recognize and acknowledge students as individuals (with their own (psychological) needs, goals, and values) as well as the teacher's ability to take this into account as a leader in classroom management and teaching practices. Authenticity encompasses a teacher's ability to be personal in the relationship with students and to act in accordance with their own professional values and beliefs. The third dimension, responsibility, covers a teacher's ability to take exclusive responsibility for the quality of the relationship with students. However, in a validation study testing the psychometric validity of the Relational Competence Questionnaire, the model with two factors proved to be more appropriate: respect for individuality and responsibility.

Teachers' beliefs about social and emotional learning in relation to their relational competence

Developing and maintaining relational competence requires teachers' willingness to act as reflective practitioners: to reflect on their actions so as to engage in a process of continuous learning (Schön, 1987). However, teachers have various beliefs about their professional role that determine their willingness to act reflectively in their classroom management and teaching. Teacher beliefs are indicative of their perceptions and judgments, which, in turn, affect their teaching practices (Pajares, 1992). It is thus reasonable to assume that teachers' beliefs about social and emotional learning are closely linked to their relational competence since they shape their practice, determine their emphasis on students' comprehensive development, their responsive and attuned interaction and their awareness of their role as models of social and emotional competence to students. Teachers' beliefs about the importance and effectiveness of social and emotional learning influence their instructional practices and classroom management strategies; when teachers value social and emotional learning, they are more likely to integrate it into their teaching, focusing on students' emotional well-being and interpersonal skills (see Jennings et al., 2013; Zinser et al, 2014). Teachers who hold positive beliefs about SEL recognize that education is not just about academic achievement but also about nurturing students' social and emotional growth. Such beliefs are likely to encourage teachers to create a holistic learning environment that addresses students' emotional needs and helps them develop essential life skills. In addition, teachers with strong beliefs in social and emotional learning are more attuned to student emotions and social dynamics (Merritt et al, 2012). This alignment enables them to respond effectively to students' emotional cues, offering support when needed and creating a safe space for students to express themselves.

Brackett et al. (2011) described three dimensions of teachers' beliefs about social and emotional learning: comfort (sense of confidence in enhancing social and emotional learning); commitment (motivation to learn about enhancing social and emotional competencies); and culture (schoolwide support for SEL). Based on the assumption that teachers' beliefs about social and emotional learning play a pivotal role in shaping their relational competence, the aim of the present study was to investigate the predictive role of various dimensions of teachers' beliefs about social and emotional learning on their relational competence and its dimensions: respect for individuality, and responsibility for the relationship. Since enhancing social and emotional competencies is crucial in all educational settings, from preschool to higher education, our hypotheses about the relationship between teachers' beliefs about social and emotional learning and their relational competence were tested on a diverse sample of teachers from a range of educational levels: kindergarten teachers, elementary school teachers, upper secondary teachers and higher education teachers. The following hypotheses were tested:

Hypothesis 1: Comfort with delivering SEL instruction (**H1a**), commitment to learning about and teaching SEL (**H1b**), perception of how much the school culture supports SEL learning (**H1c**) and understanding and perception of the importance of SEL (**H1d**) positively and significantly predict teachers' relational competence.

Hypothesis 2: Comfort with delivering SEL instruction (**H2a**), commitment to learning about and teaching SEL (**H2b**), perception of how much the school culture supports SEL learning (**H2c**) and understanding and perception of the importance of SEL (**H2d**) positively and significantly predict teacher's respect for individuality.

Hypothesis 3: Comfort with delivering SEL instruction (**H3a**), commitment to learning about and teaching SEL (**H3b**), perception of how much the school culture supports SEL learning (**H3c**) and understanding and perception of the importance of SEL (**H3d**) positively and significantly predict teachers' responsibility for the relationship.

Method

Our final sample consisted of 185 kindergarten teachers (19.5 %), elementary school teachers (29.7 %), upper secondary school teachers (25.9 %) and higher education teachers (24.3 %). Most of the participants were female (80 %), and the average age of the participants was 45.31 years (SD = 10.39). The average job tenure was 20.21 years (SD = 10.68). Most of the participants had obtained a master's degree (43.8 %), followed by participants with a Ph.D. (24.3 %) and a bachelor's degree (16.2 %).

We collected data from individuals participating in a training/educational module pertaining to artificial intelligence or social emotional learning, using an anonymized online survey. To assess participant's attitudes towards social and emotional learning, we used a Slovenian translation of the Teachers' Beliefs About Social and Emotional Learning Scale, developed by Brackett et al. (2012). The scale uses four items to measure comfort with delivering SEL instructions (sample item: "I feel confident in my ability to provide instruction on social and emotional learning"; α = .84); four items to measure commitment to learning about and teaching SEL (sample item: "I would like to attend a workshop to learn how to develop my students' social and emotional skills"; α = .91); and four items to address participant's perception of how much the school culture supports SEL learning (sample item: "The culture in my school supports the development of children's social and emotional skills"; α = .75). For the purposes of the study, we developed three additional items to measure participant's level of understanding and their perception of the importance of social and emotional learning (sample item: "Social and emotional learning is of great importance in school and educational contexts."; α = .86).

To measure participant's relational competence in the professional context, the Teacher's Relational competence scale was used (Kerman & Vidmar; 2016). The scale uses 10 items[3] (α = .86), rated on a 5-point Likert agreement scale. Furthermore, six items address teacher's responsibility for the relationship with students (sample item: "As a teacher, I take full responsibility for the quality of the student-teacher relationship", α = .78), and four items address the teacher's respect for the individuality of their students (sample item: "I take into consideration that each student experiences a given situation from a different perspective"; α = .82).

To test our hypotheses, we carried out separate multiple regression models for each dependent variable (teacher's relational competence, teacher's responsibility for the relationship, and teacher's respect for the individuality of their stu-

[3] One reverse-coded item was excluded from the analysis because of low inter-item correlations.

dents), including the dimensions of teacher beliefs about SEL at the same time ("enter" method).

Results

Descriptive statistics and correlations between variables of interest can be found in Table 1.

Table 1
Descriptive statistics and correlations between variables

	N	M	SD	1	2	3	4	5	6
1. Comfort	173	3.83	0.62						
2. Commitment	173	3.92	0.73	.321**					
3. Culture	173	3.72	0.56	.377**	.334**				
4. Understanding & importance	172	4.01	0.56	.400**	.590**	.313**			
5. Teacher's relational competence	172	3.97	0.44	.423**	.431**	.288**	.381**		
6. Respect for individuality	172	4.17	0.44	.424**	.324**	.298**	.382**	.840**	
7. Responsibility for the relationship	172	3.86	0.50	.374**	.434**	.251**	.338**	.963**	.663**

An overview of the correlations reveals significant positive correlations between the dimensions of teacher beliefs about SEL and the dimensions of teacher's relational competence. Most correlations in Table 1 could be considered moderate, while some low (e.g., between responsibility for the relationship and culture) and high degree (e.g., between respect for the relationship and responsibility for the relationship) correlations were also observed.

When predicting teacher's relational competence, the multiple regression model performs significantly better than the null model ($F (4, 166) = 16.89$; $p < .001$). Together, the variables explain 28.9 % of variance in teacher's relational competence ($R2 = 0.289$).

Table 2
Multiple regression model predicting teacher's relational competence

	B	S.E.	β	t	p
Constant	2.14	0.26		8.24	<.001
Comfort	0.21	0.05	.29	3.88	<.001
Commitment	0.17	0.05	.28	3.35	<.001
Culture	0.03	0.06	.03	0.46	.65
Understanding & importance	0.07	0.07	.09	1.05	.29

Teacher's relational competence was positively and significantly predicted by their comfort level with delivering SEL instruction and commitment to learning about and teaching SEL, thus supporting hypotheses H1a and H1b. However, opinions about how much the culture of the school would support SEL programming, as well as participant's understanding of SEL and their attitudes towards the importance of SEL did not significantly predict teacher's relational competence. Thus, our results did not provide support for Hypotheses H1c and H1d.

Next, we examined the hypotheses pertaining to the dimension of Respect for individuality. The multiple regression model explained 23.2 % of variance in the variable (R2 = 0.232) and performed significantly better than the null model (F (4, 166) = 13,81; p < .001).

Table 3
Multiple regression model predicting teacher's respect for individuality

	B	S.E.	β	t	p
Constant	2.32	0.27		8.70	<.001
Comfort	0.21	0.06	.29	3.79	<.001
Commitment	0.06	0.05	.10	1.14	.255
Culture	0.07	0.06	.08	1.08	.283
Understanding & importance	0.14	0.07	.18	2.09	.038

The results lend support for Hypotheses 3a and 3d, showing that comfort level with delivering SEL instruction, and participant's understanding of SEL and their attitudes towards the importance of SEL significantly and positively predicted teacher's respect for individuality. However, the results do not support Hypotheses 3b and 3c, as participant's commitment to learning about and teaching SEL and their opinions about how much the culture of the school would support SEL programming do not significantly predict their respect for student's individuality.

Finally, we examined whether attitudes towards SEL predicted the dimension of responsibility for the relationship. Together, attitudes towards SEL explained 25.6 % of variance in responsibility for the relationship (R2 = .256). The model was significantly better than the null model in predicting responsibility for the relationship (F (4, 166 = 14.26; p < .001). Again, the results revealed that the comfort level with delivering SEL instruction and commitment to learning about and teaching SEL significantly and positively predict teacher's responsibility for the relationship (see Table 3), providing support for Hypotheses 2a and 2b. Neither opinions about how much the school culture would support SEL programming, nor participant's understanding of SEL and their attitudes towards the importance of SEL significantly predicted responsibility for the relationship. In other words, our results did not support Hypotheses 2c and 2d.

Table 4
Multiple regression model predicting teacher's responsibility for the relationship

	B	S.E.	β	t	p
Constant	2.03	0.30		6.72	<.001
Comfort	0.21	0.06	.26	3.31	.001
Commitment	0.23	0.06	.33	3.91	<.001
Culture	0.01	0.07	.01	0.11	.916
Understanding & importance	0.03	0.08	.04	0.42	.678

Discussion

The impact on student development of systematic efforts to enhance social and emotional learning in educational contexts has been a popular area of research in recent years. However, the present study has taken a distinct route, exploring the relationship between teachers' attitudes toward social and emotional learning and their relational competence. In the following discussion, we will review the findings, implications, and future avenues based on the results.

The present study aimed to explore how various attitudes towards social and emotional learning could potentially predict different aspects of teachers' professional relational competence, namely, their relational competence as a whole, their respect for students' individuality, and their responsibility for the teacher-student relationship. The demographics of the sample reveal a majority of female participants, which is consistent with the gender distribution in the teaching profession. The array of educators included in the sample – from kindergarten to higher education – provides a comprehensive view of the educational spectrum.

An overarching observation is that the two most consistent predictors of positive teacher relational outcomes were teachers' comfort with supporting social and emotional learning and their commitment to learning about and enhancing social and emotional learning. These findings suggest that teachers who are confident in their abilities to enhance students' social and emotional competencies and are committed to ongoing training related to competence enhancement are more likely to develop and maintain positive relationships with students. Brackett et al. (2012) found that teachers who report greater comfort with and commitment to social and emotional learning also reported a higher sense of accomplishment in teaching and higher levels of self-efficacy. It is thus likely that the relationship between comfort with social and emotional learning and commitment to it, on the one hand, and relational competence, on the other, is mediated by teachers' self-efficacy; teachers with higher self-efficacy are more likely to demonstrate resilience, anticipate optimistic outcomes and take responsibility for their relationships with students. Further studies could investigate the role of self-efficacy in the relationship between teachers' beliefs and their relational competence.

Supporting Hypothesis 1a and 1b, teachers' comfort and commitment were significant predictors for overall relational competence. This underlines the importance of teachers being comfortable and confident with enhancing social and emotional learning, and it implies that enhancing teacher comfort and commitment could foster better teacher-student relationships. On the other side, school culture's support of social and emotional learning (H1c) and a teacher's understanding of the importance of social and emotional learning (H1d) were not found to be significant predictors of either overall measure of relational competence or its dimensions. This is intriguing, suggesting that personal teacher variables might have more influence on relational competence than the broader school culture as they perceive it. Alternatively, there could be a disconnect between what schools promote in terms of social and emotional learning and how teachers perceive these initiatives However, further studies are needed to explore this assumption.

In terms of respect for student individuality, Hypotheses 2a, and 2d were supported. Comfort with enhancing social and emotional learning, and understanding its importance play a role in teachers acknowledging and valuing each student's unique perspective and individuality. Contrary to expectations, commitment to SEL (Hypothesis 2b) did not predict respect for individuality, suggesting that commitment alone does not translate into this aspect of relational competence. While the participants' understanding of social and emotional learning and their attitudes towards its importance did not predict the overall measure of relational competence and responsibility for the relationship, these factors did have an impact when it came to respecting student individuality. Interestingly, the results did not support Hypothesis 2c, suggesting that the perception of school culture's support for social and emotional learning is not significantly related to this dimension of relational competence.

The results also indicate that while teacher commitment to and comfort in teaching social and emotional competencies predict their sense of responsibility in the teacher-student relationship (supporting Hypotheses 3a and 3b), the perception of school culture's support (H3c) and their understanding of the importance of social and emotional learning (H3d) did not. It seems that while personal investment in social and emotional learning is crucial for fostering responsibility in relationships, attitudes arising from the broader school environment may not play as pivotal a role.

Limitations and implications

Several limitations should be considered when interpreting and generalizing the results of the present study. Cross-sectional research design represents a major limitation in interpreting the nature of the relatedness between constructs, as it does not allow conclusions about the direction of relations. Teachers' beliefs about social and emotional learning and their relational competence are very likely in a reciprocal relationship, whereas our research design does not enable conclusions about the strength of directions in both ways. In addition, the results are affected by common method bias since all variables were operationalized as self-reported measures. Moreover, the use of the Slovenian translation of the Teachers' Beliefs About Social and Emotional Learning Scale, developed by Brackett et al. (2012), might raise questions about the cultural adaptability of the scale, considering differences in educational systems and cultural attitudes toward social and emotional learning. Future research could address this by ensuring cross-cultural validation of existing scales and, if needed, developing region-specific adaptations.

The findings of this study hold several implications for educators, policymakers, educational institutions, teacher trainings and further research in this field. There is a clear indication that teachers who are comfortable with and committed to social and emotional learning fare better in relational competence. This should encourage educational institutions to invest more in teachers' social and emotional learning, providing them safe and supportive working environment in the form of a learning community that enables learning from mistakes, sharing practices and reflecting on difficult cases (in the form of intravision or supervision), ensuring that educators are not only aware of but also confident in their own social and emotional competencies, as well as in their ability to enhance these in students. The non-significant predictive role of perceived school culture on teachers' relational competence might indicate a need for schools to reassess their attitudes and initiatives related to enhancing social and emotional learning. It would be interesting to further explore the relationship between perceived school culture and aspects of teachers' relational competence. Additionally, more insight is required on the interplay between understanding the importance of social and emotional learning and practical aspects of teaching it, as well as on the factors that contribute to teachers' personal commitment to social and emotional learning and the potential for nurturing them, especially in teacher training. The clear benefits of comfort with and commitment to social and emotional learning for relational competence underscore the need for social and emotional learning to be a cornerstone in teacher training modules. Beyond mere awareness, emphasis should be on real-life applications, scenarios, and fostering a genuine appreciation for social and emotional learning. Moreover, if replicated on a larger sample, further study could investigate the differences between teachers working at different educational levels in their attitudes toward social and emotional learning and their relational competence. Research in these areas could offer actionable insights for curriculum development at all educational levels, in teacher training, and for institutional policy-making.

In conclusion, this study underscores the significance of teachers' personal attitudes towards social and emotional learning in determining the quality of their relationships with students. As the education sector continues to recognize the importance of social and emotional learning, it becomes crucial to equip teachers not just with tools that enable enhancement of students' social and emotional competencies but also with the confidence and commitment to use them. This subtly emphasizes that social and emotional learning is not just another module to be taught but a philosophy to be integrated into one's teaching ethos.

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