Discover Education

RESEARCH Open Access

A social lens on AI in higher education: perceptions of dehumanization, skill development, and well-being

Budur Turki Alshahrani[1,2*], Faezeh Karimi[2] and Salvatore Flavio Pileggi[2]

*Correspondence:
Budur Turki Alshahrani
budurturkim.alshahrani@student.uts.edu.au
[1]School of Computer Science, University of Technology Sydney, Sydney, NSW 2007, Australia
[2]Department of Management Information Systems, Jazan University, Jazan 45142, Saudi Arabia

Abstract

Artificial Intelligence in education (AIED), particularly following the emergence of generative AI, has sparked increasing debate not only for increasing efficiency and productivity in academia but also its broader social implications. While discussions on AIED often focus on its potential benefits, increasing attention is being given to broader social concerns, including the risk of dehumanization, the development of skills, and overall well-being. These aspects remain insufficiently addressed in current literature. To explore these aspects and address this gap, the study proposes a research model that utilizes Stimulus-Organism-Response (SOR) as a structural framework and introduces a new conceptual model – Dehumanization-Skills-Wellbeing (DSW). The model captures the complex dynamics of AIED with these key social pillars. Drawing on survey-based data collected from students and instructors across higher education institutions in Saudi Arabia, findings indicate that higher levels of AIED use, often including generative AI tools, are positively correlated with empathy, support, and belonging that collectively reflect lower perceived dehumanization. These human factors are further associated with lower levels of anxiety, depression, and social isolation. Additionally, while cognitive skills development such as critical, technical and creative show a significant correlation with AI use, the impact on non-cognitive skills such as socio-emotional and collaborative skills remains unsupported and warrants further investigation. By examining these interconnected aspects, the study offers deeper insights into the ways AI may shape the social and emotional fabric of educational environments and guides the development of more human-centered and socially responsible AI adoption in higher education.

Keywords Artificial intelligence (AI), Higher education, Social impact, Dehumanization, Socially responsible AI, Human-centered learning, Well-being

1 Introduction

Artificial Intelligence in Education (AIED) has rapidly emerged as a transformative force for its potential to revolutionize academic efficiency, accessibility and productivity. According to 2025 [55] report, about 92% of students now use AI tools for their studies

© The Author(s) 2026. **Open Access** This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by/4.0/.

which was about 66 % in 2024. This dramatic increased in AI's use in education is also reflected in the global AI in education market, which was valued at 2.5 billion dollars in 2022 and is projected to reach 88.2 billion dollars by 2032 [4]. key part of this growth is the spread of generative AI tools, such as ChatGPT, which help to generate content, answer questions, and provide writing and study support.While this expansion signals the growing influence and perceived benefits of AI, it also raises critical concerns about its broader social implication [13]

The integration of AI across higher education become instrumental across multiple educational settings, extending beyond simple digitization to reshape teaching, learning, research and administrative practices. In teaching settings, AI has influences course design, personalized content delivery, assessment strategies and support higher order thinking and authentic learning tasks (?) [11]. In learning settings, AI tools allow adaptive and personalized system that enables student to engage with a content tailored to their individual needs. Additionally, AI has been widely adopted in administrative and research context to support grading, task management, data analysis, literature synthesis, rising a parallel concern privacy and ethical governance [135].

Beyond these applications, the higher education environment is undergoing more profound transformation due to the rapid development of AI enabled and immersive technologies. These shifts have intensified generational and experiential differences between instructors often describe as "digital immigrants" and student commonly referred to "digital natives whose familiarity with interconnected digital ecosystems challenges transitional linear instructional models and accelerates the adoption of technology -mediated, interactive learning environment [11, 27]. More recently, purpose-specific virtual reality VR and Metaverse technologies have emerged as advanced form of AI-enabled educational environments, especially for instructors,where high fidelity digital simulation support preservice training through immersive and real time visualization [158]. These environments enables skill development while encouraging institutional transition toward technology oriented setting. While such technologies offer clear pedagogical advantages, their increasing reliance on simulated interaction and automation also raises important questions regarding human presence, relational support, and learner's well-being [95].

In parallel, the rapid diffusion of generative AI and immersive systems has introduced broader ethical and epistemological challenges of higher education, particularly in rapidly digitizing regions [11, 158]. The widespread adoption of large language models,such as ChatGPT, has amplified concerns related to algorithmic bias, data privacy, academic integrity and reshaping the knowledge acquisition highlight the need for more balanced and responsible adoption for AI technology [76, 111, 199]. Collectively, AI is not merely as a technological enhancement, but as a socio-technical system that reshapes educational experiences, institutional practices, and human relationships which highlight the importance of examining AI in higher education through an integrated lens of overly looked dimension like for dehumanization, skill development, and well-being [43, 111, 199].

One of the social dimensions that requires deeper investigation is the potential for dehumanization within AI-integrated educational settings [43, 93, 166].Researches show a concern that technologies,including AI, serves as an infrastructure for dehumanization [134, 166]. While AI can streamline administrative tasks and personalize learning, there

is a legitimate concern that an over-reliance on these technologies could diminish crucial instructor -to-student interactions and relationships with peers, thereby impacting the social-emotional aspects of learning [78, 166].

Additionally, the development of the skills in AI-driven world presents another complex area that need to be adequately explored. According to a number of previous studies [111, 137, 143, 165], AI tools can significantly enhance cognitive skills by providing instant accessibility to information and offering more personalized learning experiences. However, the influence on skills, such as critical reasoning, socio-emotional and collaborative abilities, is still unclear and requires further exploration [52, 193]. Some studies suggest that over-reliance on AI tools might negatively affect interpersonal skills and emotional intelligence [183]. On the other hand, some studies showed that AI is empowering the developing for skills such as technical and creative skills [21, 98]. Therefore, a deeper investigation is needed comprehensively understand the impact of AI on both cognitive and non-cognitive skills.

Importantly, well-being as another important social dimension has received significant attention in the current literature [191, 199]. Well-being in the learning environment is a multi-faceted construct that encompasses the mental and social well-being of the learner, faculty, and staff [95, 113]. With growing numbers of institutions adopting technology-driven solutions, there is a need to take cognizance of potential impacts upon the well-being of all the players involved [95]. Anxieties, depression, and loneliness can be experienced by any educational stakeholders at all levels of the learning environment, impairing productivity, participation, and overall institutional culture [95, 199]. Creating an environment that fosters mental health resources and social connections can do much to create a humanized learning community [95]. Addressing the overall well-being of the student, faculty, and staff in a technology driven environment can work magic in creating a better, positive, and productive learning environment [95]

To address the critical gap in understanding the broader social implications of AIED, this study adopts the Stimulus–Organism–Response (SOR) framework [105] as a structural foundation. Stimulus consists of both AIED, exemplified by the use Generative AI, and the broader organizational factors such as ethical policies, cultural norms, institutional readiness, and competitive pressures that also paly significant role in shaping the educational environment. The organism is conceptualized through the newly developed theory of Dehumanization, Skills, and Well-being (DSW), which encompasses the social and psychological dynamics experienced by educational stakeholders. The response shows that clear understating for how the interaction between stimulus and organism factors may lead to shape a better humanized and socially responsible educational environment. By integrating these dimensions, the model provides a systemic approach to investigating how AI reshapes the social dynamics of higher education and how its adoption can be steered toward more sustainable and human-centered outcomes aligning with the United Nations' Sustainable Development Goal 4 (SDG 4) [53] for inclusive, equitable, and quality education.

To gain a deeper and more empirically grounded understanding of these dynamics, a survey was conducted among instructors and students in higher education settings [126]. The results show that perceived use of AI technologies is correlated with perceived dehumanization, as well as skill development and well-being (Sect. 5.2.3). The findings present a systematic evaluation of whether and how AI use contributes to or hinders

socially meaningful educational experiences. Consequently, the study offers evidence to inform more socially responsible and human-centered AI adoption within higher educational institutions.

Structure of this paper. It begins with the theoretical background that frames the study (Sect. 2), followed by the research methodology (Sect. 3). The proposed conceptual model is then introduced as a basis for understanding the study's core constructs (Sect. 4). This is followed by the analytical approach used to examine the data collected (Sect. 5). The results are then presented and discussed in a section6 reflecting on the relevant existing literature. The paper concludes by outlining key limitations and directions for future research (Sect. 7).

2 Theoretical background and conceptual lens

This section provides the foundation for examining the impact of AI in educational settings through a socio-technical lens [157]. It also contributes to the broader discussion on the social implications of AI that seems to be overlooked amid the rapid technological expansion. This section is structured around four core components: the disruptive nature of AI in education and the corresponding social response articulated through three key pillars which are dehumanization, skill development, and well-being(DSW). These elements are central to understanding the socio-educational dynamics shaped by AI and are aligned with the foundational blocks of the framework introduced in Sect. 4.

2.1 AI as a disruptive technology in higher education

Disruptive technology is the term used to describe the disruptive impact of new technology within a particular domain [139]. Most interpretations of this concept suggest that the traditional operations of any system are altered and transformed by emerging technologies, without any negative consequences on the distribution [76, 139]. Additionally, numerous scholars concentrate solely on the transformative computational power, immense data capacities, and technological advancements. Nevertheless, there are those who dispute the potential for these technologies to revolutionize all sectors, including education.

AI is not a new phenomenon; it has been known since seventy years ago [77]. This technology has become more accessible and faster to use and available at a higher speed,particularly after the release of generative AI tools like ChatGPT [23], which makes it so disruptive. There is no universally accepted definition of AI technology [77, 78]. Several academic researchers emphasize the difficulty of defining AI because it include a variety of multiple techniques that replicate human cognitive processes or decision-making capabilities [78]. However, a simplified interpretation of the definition is a technology that performs tasks require human intelligence [9, 78]. AI is considered the most disruptive technology and it has had a significant impact on various sectors including education [139].

The educational sector experiences deep transformation through AI because it brings both promising opportunities and substantial challenges [196]. The technology provides substantial potential to increase educational accessibility while making personalized learning scalable and improving teaching methods to reach specific learning targets [76, 78]. The extensive data analysis capabilities of AI support researchers in their efforts to enhance efficiency and productivity [26]. AI demonstrates strong potential to simplify

administrative operations through its ability to enhance admissions procedures and schedule courses better and reduce student dropout and improve retention rates [9, 76, 77].

This disruptive aspect of AI in education is defined in a paradoxical manner: it is the esthetic efficiency and scalability of AI systems and at the same time this threat to the social composition of educational spaces [78]. This paradox necessitates an intellectual prism that should be in a position to not only take into consideration the technology use, but the human implications of such use. This study introduces this prism by harmonizing AI technologies as the stimuli of the surroundings and induce internal cognitive and affective responses, which results in behavioral and institutional outputs [80]. In this context, the aspect of the related to which students and instructors feed and receive feedback on AI will be the medium through which social implications can be learned.

Addressing these concerns necessitates a shift from the techno-centric evaluation to socio-technical evaluation [157]. References [9, 78] suggest that looking at AIED not only from pedagogical and technical aspects but including ethical, legal, and societal aspects should be included in conceptual frameworks. Accordingly, this work responds by introducing three socially grounded concepts explained in Sect. 2.2.

2.2 Responding to AI disruption through key social pillars

As the integration of AI becomes more prevalent in higher education, there is a growing social concerns that need to be considered [7, 9, 78]. This study responds to that need by identifying three conceptual pillars,dehumanization, skill development, and well-being (DSW), to understand how AI reshapes the educational experience [7, 42, 60]. These pillars were not randomly selected; they emerged through a careful review of literature, theoretical alignment with socio-technical systems thinking [6, 157].

2.2.1 Dehumanization as a core social signal

The process of dehumanization occurs when people lose their human characteristics because of technological advancements [58, 70]. The rapid technological integration throughout all social sectors has shifted educational priorities from human values to efficiency and automation [1, 166]. Education serves purposes beyond knowledge transmission because it includes socialization and emotional growth and personal development [88]. The implementation of AI has sparked academic concerns because it might reduce educator involvement which remains essential for student holistic development [60].

Rather than viewing dehumanization as an abstract philosophical concern, this study treats it as a measurable variable that captures perceived losses in empathy, emotional connection, social support, and belonging [70]. These factors are essential for fostering inclusive, engaging, and ethically grounded educational environments [43]. In AI-mediated contexts, where algorithmic systems might replace or mediate interpersonal interactions, assessing the presence or erosion of these humanizing factors becomes critical.

2.2.2 Rethinking skill development in the age of AI

The pervasive presence of AI necessitates the cultivation of entirely new Competencies. AI tools can both support and substitute cognitive effort [52, 111]. As a result, the development of skills such as critical thinking and creativity, communication and emotional resilience may be either enhanced or diminished depending on design and use [167].

The integration of AI into learning spaces extends its horizons beyond cognitive and technical proficiency to cover the complex domain of social skills [111, 183]. AI presents prospects for enhancing social-emotional learning (SEL) [160] and also poses risks that demand awareness and vigilance on behalf of human interaction and social development [111].

AI technologies can be applied to enable social skill development via personalized and responsive interventions. For instance, AI-powered websites can assist educators in creating personalized social-emotional learning activities, offering learners a site on which to practice empathy, self-regulation, and social competence under a controlled regimen [125, 193]. However, there are fears that AI can diminish required human interaction which is a key to naturally acquired social skill development.

2.2.3 Well-being as a societal imperative

The psychological definition of well-being includes multiple dimensions which satisfy fundamental requirements and create contentment beyond disease absence [48]. Modern and recent research defines well-being as a positive state which enables human flourishing and optimal functioning while showing minimal psychological distress [48, 113]. This holistic perspective emphasizes complete well-being through the integration of psychological elements with social components which determine individual functioning and quality of life.

Recently, higher education institutions prioritize student well-being more than ever before [48, 199]. The student population during this period ranges from 17 to 24 years old. The age of 17-24 marks a crucial period for psychological issues to develop according [48, 113]. Research indicates that numerous students experience psychological problems including psychological distress, anxiety, depression and burnout [48, 113]. Academic performance and drop-out probability show direct relationships with these psychological issues [48, 199]. The importance of well-being extends beyond students because instructors need equal attention to their mental health and well-being.Recent studies [30, 45] shows that university teaching staff experience higher stress levels and burnout because of excessive workload and institutional demands which negatively affects teaching quality and student engagement and learning outcomes. The importance of educational stakeholders' well-being requires attention because it motivates additional research.

2.3 Addressing human and social concerns through an integrated conceptual framework

This section focuses on establishing the theoretical and conceptual frameworks that guide this study: the Stimulus-Organism-Response framework and the Dehumanization-Skills-Well-being (DSW) conceptual model. It contributes to the broader discussion on the social implications of AI that seems to be overlooked amid rapid technological expansion.

- The Stimulus-Organism-Response as Structural Framework SOR framework, originally developed in environmental psychology, provides a structured lens to examine how external stimuli affect individuals' internal psychological states and behavioral responses (organism) and lead to observable responses [80, 140]. In the context of the study, SOR frameworks serves as a structural foundation that organize and shape the research model. The stimuli is specifically defined by the rapid

emergence and integration of Generative AI, which reflect a unique technological momentum that entirely reshape traditional educational settings. Additionally, the broader organizational factors such as ethical policies, cultural norms, institutional readiness, and competitive pressures that contribute highly reshaping and governing the technology mediated new educational environment (Sect. 4.1.2). By adopting the SOR framework, this study moves beyond examining AI in isolation to understanding how AI adoption is mediated by institutional and organizational factors, and how these combined stimuli affect the psychological and social dimensions of the educational experience and the response resulting from that integration among the organism component.More details on how this the study adopt this structural model provided in Sect. 4.

- DSW Conceptual Model: Addressing a Critical Gap. Given the background discussed earlier in the paper, DSW components emerge as essential factors that needs to be discussed in an integrated way given the social concerns around them. The model adopt a multi-dimensional theoretical lens that integrates Dehumanization theory [70, 133], humanistic learning theory [88] and socio- technical system (STS) thinking [157, 201] to evaluate the social implication of AIED. Drawing on the Humanistic learning Theory, the lens prioritizes "whole person", emphasizing that the cognitive growth can not being separated from the emotional and social well-being [38, 88]. This is complemented by STS thinking, which highlight that technological interaction (Technical subsystem) and human social structure (Social subsystem) must optimized together to achieve sustainable and responsible outcomes [157]. Finally, Dehumanization factor, inspired from the dehumanization theory [133, 166], provide the critical filters to assess weather AI adoption preserves or undermine "human essence" of the educational experience. Together, these theories form a cohesive conceptual foundation, justifying the DSW model's focus on the interconnected nature of the social, cognitive, and affective dimensions of AI adoption. Additionally, this integrated approach is a direct response to fragmentation observed in the existing literature [92, 159], where each factor are frequently examined as an isolated variable that emphasize the need to combine these sub factors in an integrated way. The dehumanization became a fundamental DSW component based on the criticism of an educational technologies-based approach that is an efficiency-focused approach in its nature [128]. This is also applied to generative AI in mediating instructor-student and peer-peer relations systems face the danger of eroding the affective and social aspects that make up humanizing education [43, 166]. Skill is another critical factor of DSW, it differ of the other taxonomies as it specifically assess the the impact of AI on wide range of skills (Table 3). While tools like 21st-century competencies are featuring on what skills are important, DSW poses the questions:How generative AI adoption affects the development of skills among student and How does the quality of human presence in educational environments shape skill acquisition?, These questions point to the main assumption of the framework that cognitive and non-cognitive skills do not emerge in social empty space but emerge as a result of the interaction, relationship, and affective experiences of experiences of being social [111, 183]. In that way, to evaluate the effects of AI on skills, it is necessary to evaluate the context of relations and the psychological context within which the skills develop at the same time. Within the DSW framework, well-being is selected as a

critical indicators of psychological sustainability and getting significant attention in the recent literature [48, 89, 118]. Rather than viewing well-being as a static outcome, this model position it as a dynamic internal state that both response to AI usage and subsequently influences the social and cognitive dimensions of the educational experience. It demonstrates if AI based education is sustainable at the long run mentally. Dehumanization associated with lower interaction with humans can enhance isolation and anxiety [184]. Higher critical thinking ability would enhance self efficacy and reduce academic stress. This relationship justifies the reason as to why well-being should not be analyzed within the other pillars of model. The framework has operational clarity as each construct is defined by validated indicators described in Section 4. This enables social impact of AIED to be measured instead of being discussed on an abstract level. The model fills a clear gap that has been identified from recent literature which is the lack of comprehensive models that measure the full social impact and contribute actively in human-centered approach of AI adoption in educational settings [9, 76]. While existing AIED researches mainly focus on efficiency, this framework makes human centered outcomes the center o. This focus is in line with increasing calls for socially responsible AI in education [24, 33].

3 Methodology

This study adopts a quantitative approach to investigate how AIED is perceived in higher education, with a particular focus on the dimension of dehumanization, skill development, and well-being. The research process began with a comprehensive review of pertinent theories from the fields of social science, education, and information systems, looking particularly on their relevance to the social implications of technology [42, 150, 161]. This review led to the adoption of the Stimulus–Organism–Response (SOR) framework [80]. This framework, rooted in environmental psychology, provides a structured lens to examine how external stimuli (in this case, AI technology) affect individuals' internal states (organism) and lead to observable responses [80].

Drawing from SOR framework, the research model was constructed around three core blocks which are dehumanization, skill development, and well-being (DSW) representing key internal aspect that could be affected by AI in educational settings. The choice of factor in these blocks was driven by theory and empirical literature. Dehumanization theory served to reflect the perceived loss of human attributes such as belonging, support, empathy and human interaction [58, 133]. Humanistic learning theory guided the inclusion of skill developmental and well-being related variables that has been highlighted in the relevant literature [42]. Moreover, considering a more comprehensive approach, organizational factors such as ethical policies, cultural norms, and social readiness also play a major role in governing and understanding the socio-technical dynamics of AIED [14, 18, 68]. Although these factors are not the direct focus of this paper, their presence is important because of their impact on the broader educational context in light of AI integration.

The operationalization phase involved translating the conceptual model into a structured survey instrument [175], which was designed to quantitatively assess participants' perceptions of AI's impact across the three identified blocks. Each construct was measured using multiple items rated on a 5-point Likert scale ranging from Strongly

Disagree to Strongly Agree, with Prefer not to say options provided for sensitive constructs such as well-being, dehumanization, and skill development. While students and instructors both responded to items related to AIED, dehumanization, and well-being, only students were presented with skill development items, given their role as the primary learners. A detailed breakdown of item sources, modifications, and construct alignment is provided in Appendix A, Table 19. After the initial design, a pilot testing was conducted on a small group of respondents in order to identify the items' clarity, relevance, and interpretability. Pilot results were utilized in the revision in the wording of items and in the improvement in the coherence and validity of the survey.

Data were collected through a cross-sectional online survey conducted using Qualtrics in the two languages of English and Arabic. The survey was designed to capture perceptions from students and instructors across all model constructs except skill construct. Skill development questions were directed only to students as they are the primary learners, while instructors' role centers on facilitating rather than receiving skill development.The survey was distributed through several institutional channels in order to ensure maximum reach and representativeness. Participants were recruited through the following methods: (1) direct institutional partnerships with universities in Saudi Arabia, where the faculty coordinators shared a series of links to the survey in official learning management systems as well as via e-mail lists; (2) academic social networks, such as professional education groups; (3) snowball sampling, in which the first respondents in the study shared the survey with their colleagues [31, 181]. This multi-channel approach aimed to capture an adequate number of respondent and a diverse perspectives across higher educational institution and academic disciplines

A total of 1246 respondents initiated the survey. After applying data quality filters removing incomplete responses ($> 20\%$ missing data)and duplicate entries, 1,101 valid responses were retained, resulting in a retention rate of 88.4% among initiating participants.

Data analysis was carried out in two phases. Descriptive analysis with SPSS was undertaken e to present participants' demographic profile and response behaviour in summarized form, together with measures of means, standard deviation, and distribution of the data. [109] After that, structural analysis has been conducted using SmartPLS in order to test the measurement and structural models. Measurement model was tested for internal consistency, convergent validity, and discriminant validity, and the structural model for examining hypothesized relationships [96]. This two-phased analysis ensured the robustness and validity of the findings and met the study's objective of coming up with theoretically and empirically proven insights into social impact of AI in higher education (Fig. 1).

4 Research model

Our research model utilized the SOR framework as a structural model to explore the socio-technical landscape of AIED [80]. DSW elements function as essential components which match the theoretical framework (Sect. 2) to assess the diverse social aspects of AIED. The DSW components within the model create a specialized framework which represents the internal dynamics of educational systems. The model enables higher education institutions to connect AI progress with ethical human-centered principles while ensuring long-term social sustainability. Our model presentation in Fig. 2

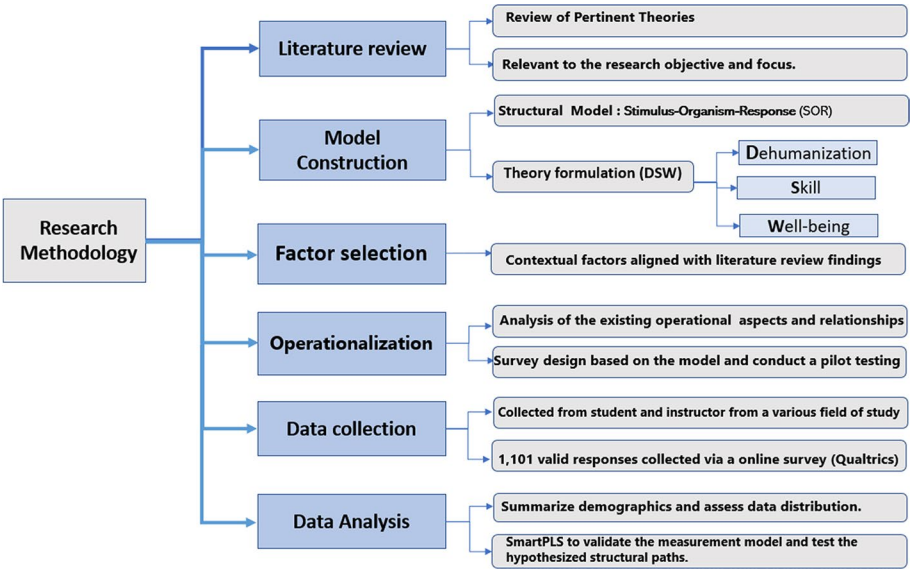


Fig. 1 Methodology flow chart

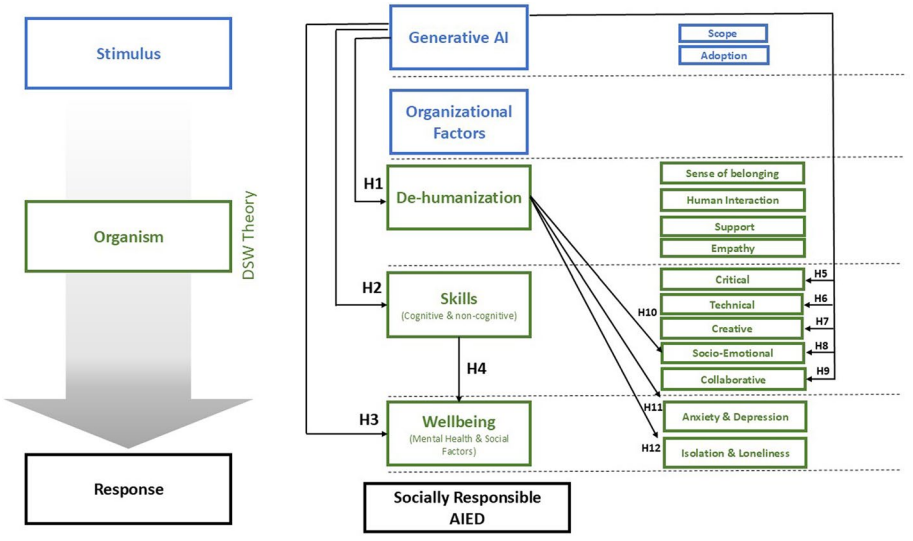


Fig. 2 Research model

follows which we explain how we built our research framework using the SOR model to handle these intricate dynamics.

4.1 Stimulus

It illustrates the external factors that influence an individual's emotions, behaviors, and perceptions [80]. In the context of our investigation, AIED, particularly generative AI, functions as a dynamic stimulus for the transformation of educational environments at the social and individual levels. Furthermore, the organizational factors (Sect. 4.1.2) that are referenced in the model are recognized as additional stimuli that contribute to socially responsible AIED. The subsequent subsections will provide an explanation of the components of stimuli.

4.1.1 AIED exemplified by generative AI

In our framework (Fig. 2), AIED acts as the main stimulus, highlighting its fast growing application in educational settings. Lately, there has been a many publications in the literature examining the possibilities that emerging Generative AI tools, especially ChatGPT, hold for changing the educational landscape [52, 59]. Stakeholders' views on AI adoption show a blend of enthusiasm and apprehension regarding its ability to modify the educational environment [9, 171]

This construct has been operationalized by focusing on two main factors, which are adoption and the scope of generative AI. These factors have been adapted from the diffusion of innovation (DOI) [149] and the Technology Acceptance Model (TAM) [102]frameworks (Table 1). These factors are essential for comprehending the extent of AI's application and the manner in which it is being integrated into educational environments.

4.1.2 Organizational factors

Organizational factors are essential at the institutional level, particularly in the context of AI in education, given the ongoing debate regarding its impact. The adoption of AI depends on ethical, cultural and social factors which make up these essential block. The continuous development and adaptation of AI strategies depends heavily on organizational factors to match the changing educational objectives and values [18, 18, 171]. Despite the fact that these factors are not the primary focus of this paper, they are crucial for the development of a socially responsible approach to AIED.

These factors will be qualitatively [74, 120]examined by engaging with decision-makers and high-level stakeholders in the education system who are responsible for cultivating an environment that supports the ethical and effective integration of AI. Although this paper does not delve into the details of these factors, their descriptions are included to offer a more comprehensive understanding of their significance in the promotion of responsible and sustainable AI adoption in educational environments. All factor are outlined as follows:

- *Ethical Guideline* are context-based guidelines that are shaped by the unique challenges and needs of each field [14]. These rules typically include aspects such as privacy, conflict of interest, respect for human rights, integrity, and equity [14, 87, 162]. In the context of AI in education, these guidelines are central to ensuring that AI use is align with human dignity and maintains academic fairness. As AI increasingly mediates learning experiences, explicit ethical requirements are necessary to minimize the risks such as bias, transparency, data privacy, and unintentional consequences[14, 37].Ultimately, understanding and properly apply these principles not only mitigates ethical risks but also fosters a culture of trust,

Table 1 AIED factors

Subfactor	Description	References
Adoption	Refers to the degree to which instructors and students are incorporating Generative AI tools into academic routines. It includes familiarity with the tools and frequency of use	[149, 189]
Scope	Determines the range and variety of tasks for which Generative AI is utilized. Reflects perceived value, advantages, and risks of AI use in education, capturing a balanced perception	[144]

innovation, and responsibility, ensuring that AI continues to serve humanity's best interests.

- *Cultural Norms* refer to the shared expectations, values and behaviors which determine social interactions within specific societies or communities [110]. AI transformation requires understanding cultural dimensions because it will reshape the established norms and practices in theb traditional education system [15, 110]. In societies,where educational institutions with traditional hierarchical teacher-centered methods will face challenges when implementing AI-driven student-centered learning because this approach conflicts with established values which may lead to resistance or demand specific implementation methods [110]. AI adoption requires cultural norms as a fundamental factor to ensure these technologies enhance existing educational frameworks instead of disrupting them.
- *Social Readiness* Social readiness refers to the level of preparedness a society or community demonstrates when accepting and integrating new technologies including AI [18, 67]. Social readiness differs from technical readiness because it examines how people feel about new technologies and their cultural fit rather than their technical capabilities [18, 67]. Higher education institutions need to focus on social readiness because AI will transform teaching methods and learning approaches and institutional social dynamics [67]. The implementation of highly automated tools encounters resistance in educational settings where strong teacher–student relationships are highly valued. The assessment of social readiness enables educators and policymakers to take proactive steps for introducing AI through culturally appropriate and effective methods [18, 67]. The concept remains unclear and relatively underexplored despite its significance to guide developing better frameworks to support adoption processes.
- *Competitive Pressure* Competitive pressure emerges from potential threat of losing market advantage when other market players start using AI technologies [68, 168]. The external force of competitive pressure pushes organizations to adopt innovations because they need to match their competitors' progress. Higher education institutions can preserve their competitive position through individualized learning approaches and predictive analytics for student maintenance and enhanced student service capabilities [68]. Competitive pressure functions as a key organizational factor which drives organizations to adopt AI technologies quickly [168]. The fear of lagging behind in competitive settings pushes institutions to adopt new technologies quickly even when they do not thoroughly evaluate social consequences. The understanding of this influence remains vital because it determines both the speed and method of AI implementation in higher education.

4.2 Organism

It describes how external stimuli affect the internal processes and states of individual, which is in our case students and instructors [80]. This section examines their perceptions responding to stimuli assess the impact of AIED on dehumanization, skill and well-being.

Table 2 Dehumanization factors

Factor	Definition	References
Sense of belonging	The emotional need to be accepted as a group member; contributes to motivation, engagement, and overall well-being in educational settings	[16, 62, 64]
Human interaction	The ways in which people interact, collaborate, and engage with others within real and physical settings, especially human-human interaction	[34, 197]
Empathy	The ability to identify and understand other people's feelings and emotions; critical for communication and a holistic learning environment	[44, 124]
Support	Refers to social meaningful support from interpersonal relationships that help individuals overcome challenges and maintain emotional stability	[3, 103]

Table 3 Skill factors

Skill category	Skill type	Definition	References
Cognitive	Critical thinking skills	Purposeful, self-regulatory judgment involving interpretation, analysis, evaluation, and inference; essential for academic success and future employment	[2, 52]
	Technical skills	Subject-specific knowledge or hard skills needed to accomplish tasks in domains like engineering or technology; increasingly influenced by AI tools and adaptive learning	[98]
	Creative skills	The capacity to produce original, useful, and novel ideas; associated with curiosity and non-traditional thinking. Considered uniquely human and crucial in tech-driven contexts	[117, 141]
Non-cognitive	Socio-emotional skills	Abilities related to self-awareness, emotion regulation, empathy, and interpersonal interactions; vital for academic and life success in evolving digital environments	[100, 108, 183]
	Collaborative skills	Competencies that support working with others toward shared goals, emphasizing teamwork, communication, and mutual responsibility	[39, 94]

4.2.1 De-humanization (D)

This block address and present the de-humanization concern regarding AIED, previously explained in Section 2. To quantitatively measure this construct, we looked at the relevant factors and scales to incorporate into the survey instrument. The sense of belonging, human interaction, empathy, and support, grounded in well-established social and educational literature, were selected. Table 2 presents a concise overview of each factor, including its working definition. Additionally, operationalization for each factor with the adapted items presented in Appendix A.

4.2.2 Skill (S)

AI tools specifically generative tools such as ChatGPT [138, 183] drive the development of skills. This study divides skills into two categories which are cognitive and non-cognitive (Fig. 4). The cognitive skills include critical, technical and creative abilities [176, 178]. The impact of AI on these skills to either improve or worsen them [52]. Non-cognitive skills such as socio-emotional and collaborative abilities are equally important for fostering strong relationships and effective teamwork [108]. Many concerns in the literature concerns regarding AI's limitations in emotional intelligence [111, 183], which may hinder the development of these skills. Accordingly, it is important to understand the potential effects of AIED on both cognitive and non-cognitive skills. Table 3 presents the skills included in the model along with their definitions.

4.2.3 Well-being (W)

Academia has shown an increasing interest in well-being as a fundamental human factor, especially after the integration of technologies into educational settings [48]. The transition of AI-driven environment may increase the feelings of isolation, anxiety and stress which challenge conventional support systems and may negatively impact educational stakeholders' mental health. The research investigates anxiety depression and loneliness because these mental health factors receive extensive attention in academic literature (Table 4).

4.3 Response: socially responsible AIED

Following the SOR framework, we can structure Socially Responsible AIED as a response coming out of dynamic interaction between AI technology as a stimuli and human-centric factors (dehumanization, well-being, and skill development). This response is a socio-technical direction in which AI implementation is formed by its functional capability as well as by its alignment with societal values and ethical concerns [36]. Using "socially" emphasizes a societal focus on AI adoption which is highlighting a priority for taking on AI incorporation in a way that benefits education communities while taking active actions on minimizing possibilities of harm or unintended consequences [24, 33, 36]. In this context, Socially Responsible AIED is a response that is based on utilizing the potential of educational technology while aligning its use with core social considerations, particularly those that foster human presence, support skill development, and promote well-being within educational contexts.

4.4 Hypothesized relationships

Building on the literature that highlights both the potential benefits and risks of AI in education, this study examines the relationships between AIED, exemplified by generative AI, on shaping key social educational dimensions (DSW). Prior research suggests that AI is changing the nature of human aspects in educational settings including the development of the abilities and maintaining their well-being.

To capture these dynamics, the hypotheses are structured at Higher level *(H1-H4)* focusing on the relationships between the major constructs in the model and lower or Factor level *(H5-H12)* focusing on the relationships between AIED and dehumanization and individual level sub factors (Fig. 2). The study hypothesis listed as the following:

- *H1: There is a relationship between Generative AI and dehumanization.* Generative AI tool can alter the nature of human interaction in education, potentially increasing or reducing perceived empathy, belonging, and interpersonal support [43, 49, 70]. This hypothesized relationship between AIED and dehumanization draws on socio-technical systems theory [157], which posits that technological mediation fundamentally alters the quality and frequency of human interaction.

Table 4 Well-being factors

Factor	Definition	References
Anxiety and depression	A condition marked by persistent worry, nervousness, or sadness, often linked to uncertainty about future outcomes. Can impair concentration, decision-making, and motivation, influencing academic and social functioning	[20, 152]
Isolation and loneliness	Isolation refers to lack of social contact, while loneliness is a subjective sense of disconnection or absence of meaningful relationships; both can reduce engagement and academic performance	[119, 182]

Dehumanization theory [58, 70] establishes that when technology reduces opportunities for emotional recognition, empathy exchange, and interpersonal support, individuals experience diminished human presence. This mechanism operates through displacement as AI systems mediate educational interactions, the relational substrate that fosters belonging and empathy may either be preserved or eroded. The directional hypothesis allows for bidirectional outcomes, acknowledging that AI's influence depends on implementation context [59, 78].

- *H2: There is a relationship between dehumanization and skill development.* Humanistic learning theory[42, 88] establishes that skill acquisition,particularly socio-emotional and collaborative competencie occurs through socially embedded learning processes.Thus, lacking empathy, belonging, and interpersonal support in educational environment,have been associated with reduced opportunities for developing essential skills[28, 81, 147]. Environments characterized by lower belonging, empathy, and support (higher dehumanization) provide fewer opportunities for interpersonal skill practice and feedback [29]. The causal mechanism operates through social learning deprivation: when learners perceive limited human presence, they encounter fewer authentic contexts for developing interpersonal competencies, even as cognitive skills may develop independently through AI-mediated practice.
- *H3: There is a relationship between dehumanization and well being.* The relationship between dehumanization and well-being is grounded in the belongingness theory [16, 64], which identifies social connection as a fundamental human need. When educational environments lack empathy, support, and a sense of belonging, individuals are more likely to experience unmet psychological needs, leading to anxiety, depression, isolation, and loneliness [69, 71, 86]. This pathway reflect a well-established stress mechanism that the perceived social disconnection activates psychological distress responses that impair both mental health and academic functioning.
- *H4: There is a relationship between skill development and well being.* This hypothesis draws on the competence-based model of psychological well-being [61, 132], which proposes that skill mastery,particularly socio-emotional and critical thinking competencies,enhances self-efficacy, reduces academic stress, and improves life satisfaction [169]. The causal mechanism operates through perceived competence: as learners develop cognitive and non-cognitive skills, they experience greater control over academic challenges and social interactions, buffering against anxiety and depression while fostering resilience.
- *H5: There is a relationship between Generative AI and critical skills.* Generative AI tools may support critical thinking by solving more complex scenarios,writing tasks and providing diverse perspectives, however, they may also encourage passive consumption of information [111, 143, 151, 180].Many studyies highlighted the concers aroun the the concern that excessive reliance on AI could weaken their ability to think independently and make responsible decisions [180] This relationship assesses whether AIED contributes to or detracts from learners' analytical reasoning abilities.
- *H6: There is a relationship between Generative AI and technical skills.* The integration of AI tools may increase digital literacy and technological competence by exposing

learners to advanced systems [21, 98]. Upskilling may be necessary to keep up with the rapidly changing AI technologies [179]. Understanding how AI impacts technical skills in higher education helps match industry demands with academic programs and guarantees graduates are ready for AI-driven workplaces [98]. Therefore, this hypothesis explores the impact of this type of skill.

- *H7: There is a relationship between Generative AI and creative skills.* While generative AI can inspire and provide new ideas and support creativity processes, concerns exist that it may standardize outputs and diminish originality [153, 188] This relationship investigates AI's role in shaping creativity in educational contexts.
- *H8: There is a relationship between Generative AI and socio emotional skills.* AI tools can enable virtual collaboration and emotional exchange, but they may reduce opportunities for authentic interpersonal engagement [160, 183]. This hypothesis examines whether AIAD affects learners' ability to navigate social and emotional dynamics.
- *H9: There is a relationship between Generative AI and collaborative skills.* Educational environment facilitated by technologies like AI can improve coordination and group productivity [123], yet they may also weaken the interpersonal bonds developed through face to face teamwork. Numerous studies in the literature emphasize the necessity of enhancing our comprehension of human-AI collaboration as AI becomes progressively integrated into society [34, 123]. These calls underscore the necessity of precisely evaluating the perceived impact of generative AI on collaborative abilities, ensuring that these technologies enhance our capacity for effective collaboration.
- *H10: There is a relationship between dehumanization and socio emotional skills.* Environment with lower levels of human factors such as empathy and belonging can negatively affect the development of socio-emotional competencies [43, 108], potentially impairing learners' capacity for effective interpersonal engagement. This hypothesis examines that possible connection.
- *H11: There is a relationship between dehumanization and anxiety and depression.* Perceived dehumanization has been associated with higher level of stress, anxiety, and depressive symptoms in any environment and education system is not immune [47, 86]. Therefore, examining this relationship seeks to determine whether diminished human presence in AI mediated education exacerbates these mental health issues.
- *H12: There is a relationship between dehumanization and isolation and loneliness.* When social bonds weaken due to reduced human interaction, learners may experience heightened isolation and loneliness [70, 164]. This hypothesis investigates whether dehumanization intensifies such feelings in technology driven educational contexts.

5 Results

This section presents results of both descriptive and structural analyses.The following subsections present the findings from each stage of the analysis.

5.1 Descriptive analysis

The analysis was performed to show the distribution of responses across different categories of demographic characteristics under study. This section provides an overview

of the sample characteristics, capturing information such as gender, age group, ethnic background, country of working or studying, educational level, professional role, program type, and academic discipline. In addition, descriptive statistics were computed for the core questions and the participants response analyses.

5.1.1 Demographic data

The demographic analysis [194] was performed to show the distribution of responses capturing information such as gender, age group, ethnic background, country of working or studying, educational level, professional role, program type, and academic discipline.

Notably, gender representation in the sample indicates that more than two-third of the respondents are female (59.4%), followed by males (40.1%), while a very small proportion selected Others (0.3%) and (0.3%) are missing in this category. Figure 12 indicated that female (both students and instructor/teacher collectively represents the largest proportion of the sample population. By examining each group separately (Appendix B (Fig. 3)), teachers or instructor have the same proportion across male (11.6%) and female (11.4%) respondents. On the other hand, female students (i.e., 47.9%) are twice the percentage of male students (28.0%) in the sample population. The observed gender imbalance in survey responses, with a higher proportion of female participants, is consistent with findings from multiple studies [17, 85, 170] indicating that female are generally more inclined to participate in online surveys than male. Additionally, the higher representation of female participants in this study, which primarily collected data in Saudi Arabia, reflects national enrollment trends. Female students represent a larger proportion of enrollment in higher education institutions in Saudi Arabia [50, 57].

In terms of age, results indicates that most of the respondents had an age of 26 to 30 years (25.4%). Respondents with age of 21 to 25 years and 31 to 35 years were equal in proportion, each representing one-fourth of the sample population. A smaller portion of the participants were under 20 years of age (3.4%). Respondents with ages of 36 to 40 years and above 40 years are in a considerable proportion of the sampled population (36-40: 16.1%; > 40: 12.6%). A few respondents did not disclose their age and hence considered as missing (0.7%).See Appendix B (Fig. 13)

Ethnic background and race were also examined as part of the demographic profile (Fig. 14). About 91.0% of the sampled population from West Asia/Middle East (e.g. Iran,

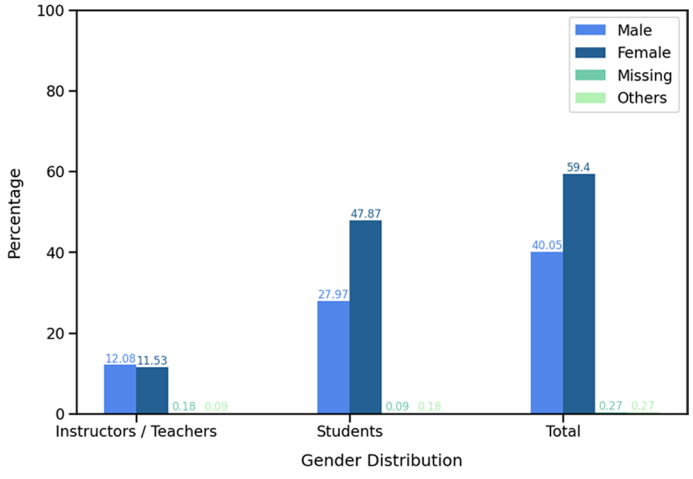


Fig. 3 Gender distribution by role

Saudi Arabia). A few respondents were also from North America (Egypt, Morocco, Sudan) (1.6%).Regarding race (Fig. 15), most respondents identified as Middle Eastern or North African (79.4%), followed by White (6.6%) and Asian or Pacific Islander (5.5%). A small percentage chose not to disclose their ethnic or racial background. A small percentage chose not to disclose their ethnic or racial background. See Appendix B (Figs. 14 and 15)

As part of the demographic profile, participants were asked to indicate the country where they are currently working or pursuing their studies (Appendix B, Fig. 16). Most of the respondents were from Saudi Arabia (92.6%), while the small proportion of the respondents were from Australia (4.0%). Some respondents were studying or working in educational institutions in other countries of the world (3.2%), including USA, UK, Malaysia, India, Qatar, Egypt, Ireland, and Jordan.

In terms of occupation (Fig. 17 in Appendix B), undergraduate students (Bachelor) were 27. 3% which represents the largest group of respondents. Master's or postgraduate students were 27.0%. Instructors or teachers made up 23.2% of the group of respondents, and PhD students made up 21.8%. About (0.7%) of the responses (0.7%) were missing from this category. The general responses reveal a diverse sample that includes both students at various levels and teaching staff.

Regarding the field of study/department, results showed that nearly one fourth of the respondents belonged to Business and Management field (19.5%). Another majority of the respondents were working or studying in the field of Information Technology and Computer Science (17.1%). Respondents working or studying in Social Science, Education, Engineering, and Medicine and Health Science were equally proportionate, each representing around 10% of the sampled population. The remaining respondents working or studying in Arts and Humanities (3.7%), Law (3.1%), 'Physical Science and Education' (1.9%), and Sciences (2.0%) field collectively represent 10% of the sampled population. A few respondents were studying or working in other field (3.1%), while some did not disclose their field of occupation (0.3%). See Appendix B (Fig. 18).

5.1.2 Core question analysis

Mean and standard deviation was computed to determine the average scores of respondents and variability in responses from the average scores (Table 20). Among all constructs, the student respondents responded lowest on the item 'AIED9' (M = 2.37, SD = 1.261), stating to be disagreed with the statement. On the contrary, the student respondents responded highest on the item 'SD1' (M = 4.44, SD = 0.903), stating to be agreed with the statement. Normality of constructs was assessed using skewness and kurtosis (Table 20)(Appendix B). As per rule, skewness between ±3 and kurtosis between ±10 indicated non-normality [25, 96]. Results indicated that all variables had the skewness scores ranging between −3 and +3 and kurtosis scores ranging between −10 and +10. This indicated normality of data.

A core question analysis was also conducted to explore participants' responses to the study's main constructs. Each construct consisted of a number of items that aimed to measure different aspects of the underlying construct. To gain a clear picture of participants' perception, item-level response distributions were graphically represented through stacked bar charts (Figs. 4, 5, 6 and 7). These graphics allowed for a detailed look at the levels of agreement, neutrality, and disagreement for each item.

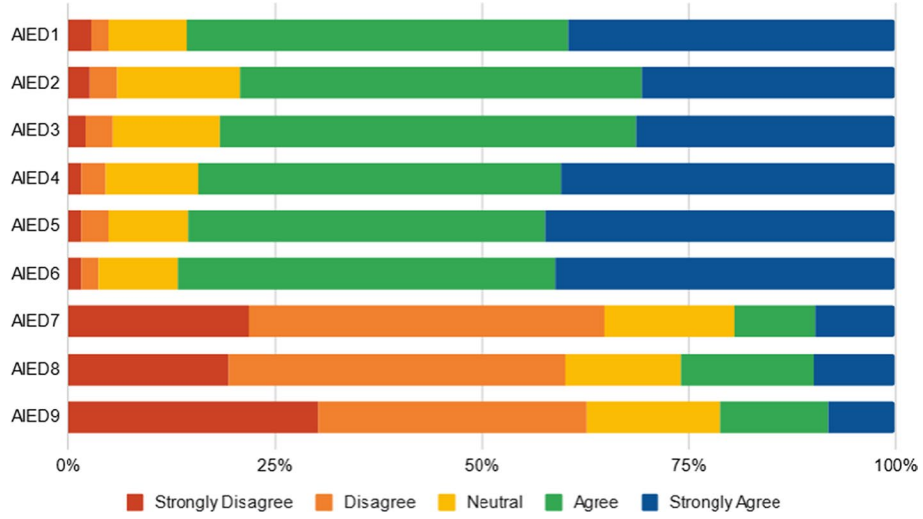


Fig. 4 Participants' responses for AIED

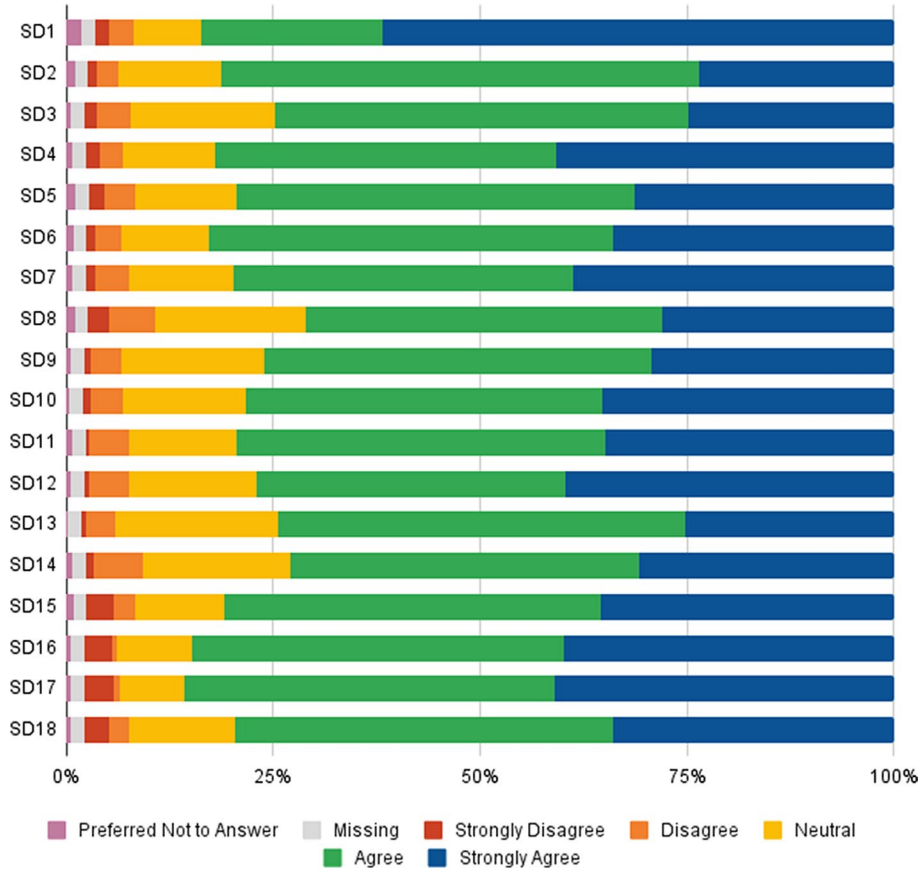


Fig. 5 Participants' responses for skill development

The first construct, AIED, captures participants' perceptions of current attitudes toward and usage patterns of AI in educational settings. Figure 4 illustrate the distribution of respondents' answers across Likert-scale categories for each item. All items from AIED1 to AIED6 gathered insights about familiarity, usage and the potential benefits of AI in education. Most of the participants highly reported to be agreed or strongly agreed

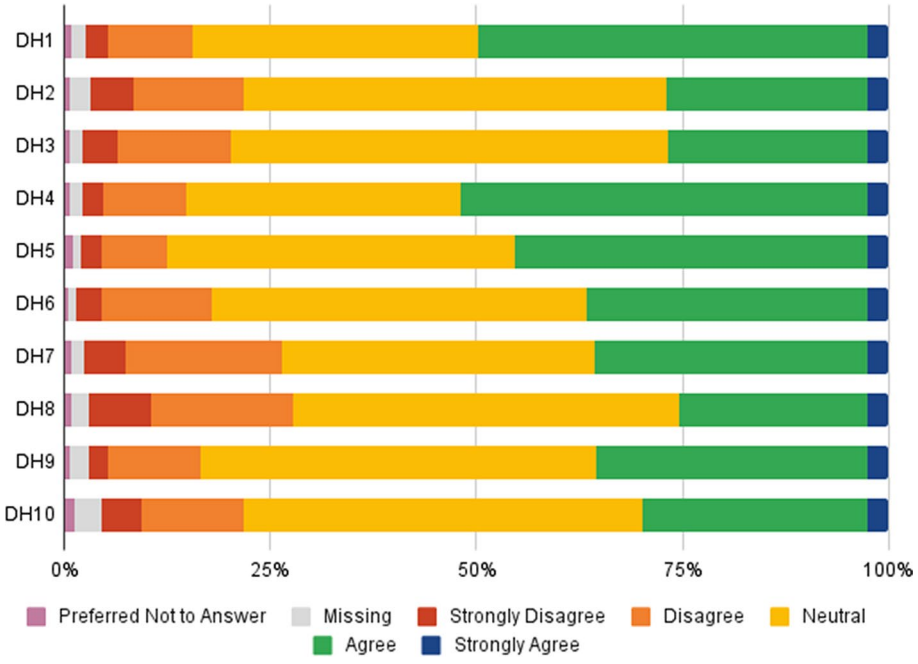


Fig. 6 Participants' responses for de-humanization

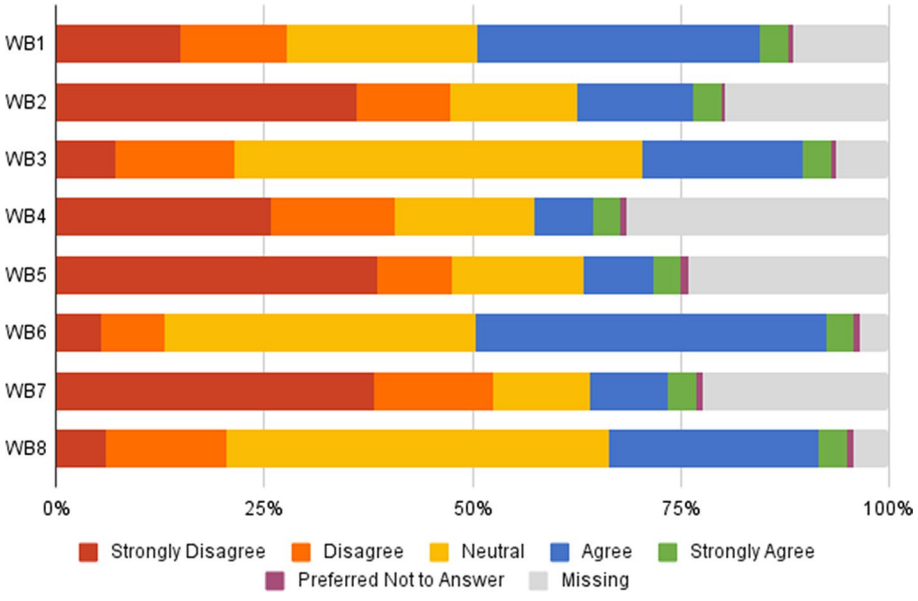


Fig. 7 Participants' responses for well-being

with the statements. For items related to the perceived or potential risks of AI in education (AIED7–AIED9), respondents largely expressed disagreement, indicating limited concern over such issues.

Skill development construct provides insights into participants' perceived competencies and areas for potential development. All items analysis from agreement to disagreement are represented in Figuer 5. This construct represented that all skill types that has been incorporated in the study which are critical (SD1–SD4), technical (SD5–SD8), creative (SD9–SD10), socioemotional (SD11–SD14), and collaborative (SD15–SD18).

Overall, all students reported a high level of agreement across all items for all skill types. Most responses clustered around agree and strongly agree, indicating a generally positive perception of their engagement with and development of these skills.

For the dehumanization construct, the items were positively worded to better capture the perception of the importance of human factors in the educational environment. As shown in Fig. 6, Participants mostly indicated agreement and strong agreement with the statements, although a noticeable proportion selected neutral responses, suggesting some variability in perceptions related to human aspects of the educational environment.

The items analysis for well-being are represented in Fig. 7. The well-being construct (WB1–WB8) reflects noticeable variation in patterns of response. Items such as WB3, WB6, and WB8 displayed higher levels of agreement, indicating that some participants were identifying experiences involving emotional tension or psychosocial unease. In contrast, items such as WB1, WB2, and WB7 showed higher levels of neutral, disagreeing, or missing scores, indicating a sense of caution or unease to respond to questions regarding to personal well-being. This variability indicates the sensitivity of the construct.

5.2 Structural analysis

It was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) to assess the measurement and structural models [25, 96]. This included preparing data for the analysis and evaluating indicator reliability, internal consistency, and validity of the constructs, and discriminant validity followed by hypothesis testing through path coefficients and significance levels.

Given that the survey design differentiated between student and instructor roles, skill development assessed only for students, two separate structural equation models were specified. The student model examined the relationships between AIED, perceived dehumanization, skill development, and well-being. On the other hand, the instructor model examined the impact of AIED on perceived dehumanization and well-being only. This separation reflects both the role distinctions between students and instructors and the structure of the measurement instrument.

Additionally, the study investigated missing data. According to Bennett [19] who advocated that the presence of significant amount of missing data (more than 10%) may cause skewness to the findings of subsequent statistical analysis. List-wise deletion was applied for three reasons: first, the retained sample (N = 1,101; 88.4%) exceeded minimum requirements for PLS-SEM analysis [66], second, the limited extent of missing data (11.6%) minimized potential bias [90], and third, sensitivity analyses revealed no significant demographic differences between excluded and retained cases ($\mathcal{X}^2$ tests, all $p > 0.15$), suggesting missingness was not systematically related to observed characteristics. While acknowledging that "prefer not to answer" responses may indicate non-random missingness, this approach balanced analytical parsimony with adequate statistical power [127]. Findings should be interpreted as representative of participants providing complete responses.Accordingly, the final valid sample size for selecting full complete response of both students and instructors/ teachers survey was 764 and 235, respectively.

5.2.1 Measurement model assessment

The reliability and validity of the measurement model were evaluated using Confirmatory Factor Analysis (CFA), assessing factor loadings, convergent validity, and discriminant validity [25].

All core constructs (AIED- Dehumanization, Skill, and Well-being) were conceptualized and modeled as higher-order constructs (HOCs), each composed of multiple reflective LOCs. All measurements were initially assessed at the lower-order construct (LOC) level, and the results are presented in Table 5. While each LOC was measured reflectively, the HOCs were modeled using a reflective–formative structure, where the higher-order construct is formed by combining the LOCs in a formative manner [65, 66] (Sect. 5.2.2). This modeling approach aligns with the multidimensional nature of the constructs and the conceptual framework of the study.

A

- *Factor loading (FL).* It represents the strength and direction of the relationship between an indicator and an underlying latent construct. [190]. Factor loadings should ideally be 0.7 or at least 0.6 [65, 173]. According to [65, 66], loadings should ideally exceed 0.70, with 0.60 considered the minimum acceptable threshold. During the assessment of the measurement model, several items, particularly from the AIED scope and well-being constructs, were found to have outer loadings below this threshold in either the student or teacher samples. As a result, all items with low factor loadings were excluded to enhance the reliability and validity of the measurement model (Table 5). Additionally, items AIED-7, AIED-8, AIED-9 and WEB-3, WEB-6, WEB-8 (See Appendix A) were reverse-coded, as they were scored in the opposite direction to other items within their respective constructs. The theoretical justification for this step lies in the operational definitions of the constructs [35, 146, 202]. For the well-being construct, which is operationalized through negative indicators such as anxiety and depression, items such as WEB-3 ("I am happy with my social relationships") represent positive states that run counter to the construct's primary valence and this apply to WEB-6 and WEB-8. Similarly, for the AIED construct, items AIED-7 ("undermine credibility"), AIED-8 ("over-reliance"), and AIED-9 ("introduce bias") reflect concerns that are conceptually opposite to the operational definition of AI adoption and positive perception. This conceptual misalignment was empirically confirmed through an 'item-total correlation' analysis for the indicators of AIED (Table 6) and WEB (Table 7), which revealed that these items had significant negative correlations with the other items in their respective scales [35]. Consequently, to ensure internal consistency and reliability, the scaling for these items was reverse-coded. Upon investigation of the measurement model, the study found that the factor loadings of items AIED4, AIED5, AIED6, were 0.668, 0.661, and 0.639 in students' survey, while items AIED7, AIED8, AIED9 those were 0.525, 0.504, and 0.350 in teachers' survey, respectively. Also, from the construct anxiety and depression, the loading of items WB1 was –0.748 in students' survey, while that of item WB1 was 0.184 in teachers' survey, respectively. In addition, from the construct isolation and loneliness, the factor loadings of item WB7 was 0.564 in teachers' survey. Since these items were lower than the minimum threshold of 0.60 as suggested by [65, 66], these items were deleted from the measurement model.

Table 5 Confirmatory factor analysis—reliability and convergent validity

	Students				Teachers			
	FL	Cronbach's alpha	Composite reliability	AVE	SFL	Cronbach's alpha	Composite reliability	AVE
AI in education								
Adoption		0.673	0.685	0.600		0.831	0.844	0.747
AIED1	0.798				0.814			
AIED2	0.787				0.890			
AIED3	0.737				0.887			
Scope		0.871	0.885	0.795		0.869	0.875	0.793
AIED4	–				0.889			
AIED5	–				0.873			
AIED6	–				0.908			
AIED7	0.882				–			
AIED8	0.911				–			
AIED9	0.881				–			
De-humanization								
Sense of belonging		0.590	0.827	0.687		0.709	0.720	0.773
DH1	0.943				0.859			
DH2	0.698				0.899			
Human interaction		0.720	0.767	0.633		0.705	0.717	0.628
DH3	0.810				0.795			
DH4	0.866				0.836			
DH5	0.703				0.744			
Support		0.669	0.721	0.586		0.781	0.798	0.695
DH6	0.847				0.877			
DH7	0.708				0.847			
DH8	0.734				0.774			
Empathy		0.626	0.629	0.727		0.684	0.707	0.758
DH9	0.838				0.900			
DH10	0.867				0.840			
Skills development								
Critical skills		0.779	0.912	0.589		N/A	N/A	N/A
SD1	0.884				N/A			
SD2	0.683				N/A			
SD3	0.768				N/A			
SD4	0.720				N/A			
Technical skills		0.777	0.789	0.595		N/A	N/A	N/A
SD5	0.788				N/A			
SD6	0.786				N/A			
SD7	0.753				N/A			
SD8	0.759				N/A			
Creative skills		0.673	0.683	0.753		N/A	N/A	N/A
SD9	0.847				N/A			
SD10	0.888				N/A			
Socioemotional skills		0.777	0.778	0.599		N/A	N/A	N/A
SD11	0.774				N/A			
SD12	0.763				N/A			
SD13	0.780				N/A			
SD14	0.780				N/A			
Collaborative skills		0.815	0.898	0.632		N/A	N/A	N/A
SD15	0.742				N/A			
SD16	0.708				N/A			
SD17	0.844				N/A			
SD18	0.875				N/A			

Table 5 (continued)

	Students				Teachers			
	FL	**Cron-bach's alpha**	**Composite reliability**	**AVE**	**SFL**	**Cron-bach's alpha**	**Composite reliability**	**AVE**
Well-being								
Anxiety and depression		0.852	0.859	0.697		0.869	0.876	0.792
WB2	0.861				0.842			
WB3	0.715				–			
WB4	0.886				0.918			
WB5	0.865				0.908			
Isolation and loneliness		0.762	0.776	0.678		0.715	0.722	0.778
WB6	0.844				0.897			
WB7	0.755				–			
WB8	0.867				0.866			

Table 6 Item–total correlation for AIED

		AIED1	**AIED2**	**AIED3**	**AIED4**	**AIED5**	**AIED6**	**AIED7**	**AIED8**	**AIED9**
AIED1	r	1								
	p-value									
AIED2	r	0.941**	1							
	p-value	< 0.001								
AIED3	r	0.755**	0.844**	1						
	p-value	< 0.001	< 0.001							
AIED4	r	0.860**	0.864**	0.699**	1					
	p-value	< 0.001	< 0.001	< 0.001						
AIED5	r	0.602**	0.587**	0.421**	0.405**	1				
	p-value	< 0.001	< 0.001	0.001	0.002					
AIED6	r	0.160	.242	.430**	.415**	– 0.008	1			
	p-value	0.238	0.073	0.001	0.001	0.956				
AIED7	r	– 0.336*	– 0.434**	– 0.186	– 0.442**	– 0.169	– 0.165	1		
	p-value	0.011	0.001	0.169	0.001	0.213	0.224			
AIED8	r	– 0.067	– 0.242	– 0.430**	– 0.059	– 0.309*	– 0.459**	0.454**	1	
	p-value	0.620	0.071	0.001	0.667	0.022	0.001	0.001		
AIED9	r									1
	p-value									

* $p < 0.05$, ** $p < 0.01$

Results indicated that the remaining items had a factor loading higher than 0.60 as suggested by Hair [65, 66] (Table 5), and hence were retained in the model.

- *Reliability* . Cronbach's alpha and composite reliability (CR) was used to assess reliability. Reliability is referred to as the extent to which a variable is being measured with its related indicators [46, 73]. According to [65, 106, 156] suggested that both Cronbach's alpha and CR values should be above 0.70 ideally, or at least above 0.60 [12, 66]. Results indicated that after deleting the items, the Cronbach's alpha of all variables ranged between 0.590 and 0.792, while the composite reliability of all variables ranged between 0.685 and 0.912 respectively (Table 5). Hence, both Cronbach's alpha and CR values met the criteria suggested by [66], indicating to have achieved reliability.

- *Convergent validity* . Average variances extracted (AVE) was used to assess convergent validity. Convergent validity is referred to as the extent to which

Table 7 Item–total correlation matrix for WB

		WB-1	WB-2	WB-3	WB-4	WB-5	WB-6	WB-7	WB-8
WB-1	r	1							
	p-value								
WB-2	r	-0.232^{**}	1						
	p-value	< 0.001							
WB-3	r	0.361^{**}	-0.333^{**}	1					
	p-value	< 0.001	< 0.001						
WB-4	r	-0.314^{**}	0.671^{**}	-0.328^{**}	1				
	p-value	< 0.001	< 0.001	< 0.001					
WB-5	r	-0.177^{**}	0.674^{**}	-0.318^{**}	$.714^{**}$	1			
	p-value	< 0.001	< 0.001	< 0.001	< 0.001				
WB-6	r	0.129^{**}	-0.069^{*}	$.151^{**}$	-0.095^{**}	-0.074^{*}	1		
	p-value	< 0.001	0.024	< 0.001	0.002	0.016			
WB-7	r	0.055	0.367^{**}	0.041	0.431^{**}	0.394^{**}	-0.334^{**}	1	
	p-value	0.075	< 0.001	0.180	< 0.001	< 0.001	< 0.001		
WB-8	r	0.057	-0.023	0.150^{**}	-0.044	-0.023	0.613^{**}	-0.317^{**}	1
	p-value	0.065	0.446	< 0.001	0.149	0.463	< 0.001	< 0.001	

$^{*}p < 0.05, ^{**}p < 0.01$

a set of indicators the measure the same construct are positively correlated [73]. As suggested by [66, 106]that AVE should be higher than 0.50. Results indicated that the AVE scores of all variables ranged between 0.586 and 0.795, respectively (Table 5), which shows the criteria suggested by [66]. These results reflected that convergent validity has been achieved.*Discriminant validity*. HTMT matrix and Fornell-Larcker criterion were used to assess discriminant validity. Discriminant validity is referred to as the extent to which one construct is empirically different from other constructs in the model [73]. Firstly, Heterotrait-Monotrait criterion or HTMT criterion identifies that the mean score of the item correlations across constructs relative to the mean of average correlation for the items measuring the same construct [73]. To achieve discriminant validity, HTMT matrix should be below 0.85 [73]. Results in Table 8 and 9 indicated that all scores of HTMT matrix were less than 0.85, which was acceptable as per [73]. Secondly, Fornell-Larcker criterion defines that AVE of each construct should be larger than all the squared inter-construct correlations between that construct and all other reflectively measured constructs in the structural model [54]. Results in Table 10, 11 indicated that all AVE scores (represented on the diagonal of the matrix) were higher than all squared inter-construct correlations (represented below the diagonal of matrix). Overall, both HTMT and Fornell-Larcker suggested that discriminant validity was achieved in both students' and teachers' data.

5.2.2 Validity testing of higher order construct (HOC)

The constructs AIED, Dehumanisation, Skills Development, and Well-being were modelled as higher-order composites formed by their respective lower-order constructs. The new variable was tested for convergent validity, collinearity assessment, and relevance in the construct [66]. Convergent validity was assessed using redundancy analysis, comparing each formative HOC with a corresponding single-item reflective measure. Results showed strong path coefficients(higher than 0.70)for all constructs ranging from 0.740 to 1.00, confirming that convergent validity has been achieved as suggested by [66].

Table 8 Discriminant validity—heterotrait-monotrait ratio (HTMT)—students

		1	2	3	4	5	6	7	8	9	10	11	12	13
1	AIED adoption													
2	AIED scope	0.151												
3	Anxiety and depression	0.208	0.521											
4	Collaborative skills	0.203	0.143	0.13										
5	Creative skills	0.324	0.046	0.277	0.699									
6	Critical skills	0.347	0.142	0.273	0.777	0.78								
7	Empathy	0.365	0.296	0.393	0.3	0.435	0.447							
8	Human interaction	0.33	0.249	0.165	0.285	0.19	0.262	0.651						
9	Isolation and loneliness	0.11	0.307	0.27	0.663	0.476	0.517	0.488	0.246					
10	Sense of belonging	0.407	0.418	0.433	0.29	0.334	0.398	0.749	0.827	0.362				
11	Socioemotional skills	0.341	0.091	0.369	0.624	0.707	0.816	0.498	0.289	0.242	0.388			
12	Support	0.472	0.347	0.274	0.362	0.285	0.263	0.789	0.694	0.397	0.809	0.387		
13	Technical skills	0.328	0.06	0.097	0.78	0.751	0.862	0.459	0.246	0.628	0.379	0.689	0.373	

Secondly, collinearity was assessed using Variances Inflation Factor (VIF). According to Hair [66] who suggested that VIF scores should be lower than 5 in order to avoid multicollinearity. Results in Table 12 indicates that since all indicators had VIF lower than 5, there was no issues of multicollinearity.

Furthermore, to validate the higher-order constructs (HOCs), PLS-SEM bootstrapping with 5,000 subsamples was conducted. As shown in Table 13, a lower-order construct (LOC) was retained if it had a significant outer weight ($p < 0.05$). If the outer weight was not significant, its outer loading has to be checked. According to [65, 66], the outer loads are considered acceptable when ($p < 0.05$) (Table 14). Thus, LOCs with either a significant outer weight or a loading above 0.50 with statistical significance were included in the model as valid contributors to their respective HOCs.

5.2.3 Path analysis—PLS-SEM

PLS-SEM analysis was conducted to assess the significance of relationships between variables in order to test stated hypotheses under study. A path is considered to be significant if its p-value is less than 0.05 or t-test statistic is higher than 1.96.To examine the hypothesized relationships, the analysis was conducted at two levels. At the first high level, all relationships were tested between the main constructs using higher-order constructs (HOCs). At the second level, a more detailed analysis was conducted based on the specific hypotheses and the focus of each construct.

- High-Level Path Analysis To evaluate the overall conceptual framework, path analysis was conducted between the higher-order constructs (HOCs) and reflect the hypothesized relationship in the research model (Fig. 2), allowing for the examination of direct relationships among the main theoretical blocks in the two models (Figs. 8 and 9). Results from PLS-SEM analysis in Table 15 indicated that AIED significantly correlates with dehumanization (Students: $\beta = 0.434$, $t = 12.598$, $p < 0.001$; Teachers: $\beta = 0.472$, $t = 6.237$, $p < 0.001$) which prove that H1 is accepted and supported. Furthermore, de-humanization significantly correlates with skills development of students ($\beta = 0.381$, $t = 3.895$, $p < 0.001$), which means that H2 is accepted. In addition, de-humanization significantly correlates with well-being of both students and teachers (Students: $\beta = -0.251$, $t = 2.325$, $p < 0.001$; Teachers: $\beta = -0.701$, $t = 15.146$, $p < 0.001$). Hence, hypothesized relationship H3 is accepted. However, skills development did not significantly correlate with well-being of students ($\beta = -0.350$, $t = 1.812$, $p = 0.058$). Hence, H4 is not accepted at high-level testing. PLS-SEM with 5,000 sub-sample bootstrapping in Table 16 also assessed the mediating role of de-humanization and skills development in the relationship between AI in education and well-being. Results from specific indirect effects indicated that de-humanization mediates the insignificant relationship between AIED and skills development ($\beta = 0.154$, $t = 5.415$, $p < 0.001$). However, skills development did not significantly mediate the link between AIED and well-being of students ($\beta = -0.018$, $t = 0.651$, $p = 0.515$). Moreover, de-humanization significantly mediated the relationship between AIED and well-being of students and teachers (Students: $\beta = -0.122$, $t = 3.201$, $p < 0.001$; Teachers: $\beta = -0.331$, $t = 5.030$, $p < 0.001$). Also, skills development significantly weakened the negative relationship between de-humanization and well-being of students ($\beta = -0.086$, $t = 2.774$, $p < 0.01$).

Table 9 Discriminant validity—heterotrait-monotrait ratio (HTMT)—teachers

		1	2	3	4	5	6	7	8
1	AIED adoption								
2	AIED scope	0.898							
3	Anxiety and depression	0.368	0.341						
4	Empathy	0.409	0.364	0.290					
5	Human interaction	0.406	0.307	0.367	0.538				
6	Isolation and loneliness	0.482	0.407	0.453	0.500	0.581			
7	Sense of belonging	0.552	0.468	0.459	0.501	0.709	0.815		
8	Support	0.467	0.418	0.446	0.65	0.571	0.819	0.785	

- Factor-Level Analysis To provide a more detailed understanding of the underlying relationships and test the hypothesized relationship, a factor-level path analysis was performed (Fig. 17). In this stage, Skills and well-being constructs were disaggregated into their lower-order constructs (LOCs) to examine factor-specific relationships. However, AIED and Dehumanization construct was retained as a higher-order construct due to their conceptual coherence and the need to test their aggregated influence on other factors. Results from PLS-SEM analysis (Table 17) indicated that firstly, AIED significantly correlates to development of students' critical skills (β = 0.277, t = 6.687, $p < 0.001$), technical skills (β = 0.229, t = 3.752, $p < 0.001$), and creative skills (β = 0.209, t = 3.960, $p < 0.001$) but did not significantly correlates to development of students' socioemotional skills (β = 0.119, t = 1.636, $p = 0.102$) and collaborative skills (β = 0.141, t = 1.132, $p = 0.258$). Hence, H5,H6,H7 were accepted, while hypotheses H8 and H9 were rejected. Similarly, AIED significantly correlates to de-humanization of students (β = 0.355, t = 6.270, $p < 0.001$) and teachers (β = 0.471, t = 6.222, $p < 0.001$). Hence, hypothesized relationship H1 is also supported at a factor level analysis. For relationship between de-humanization and well-being, the study found a statistically significant correlation with de-humanization and anxiety and depression of students (β = −0.340, t = 11.940, $p < 0.001$) and teachers (β = −0.421, t = 6.257, $p < 0.001$). Meanwhile, there was a statistically significant correlation with de-humanization and isolation and loneliness of students (β = −0.363, t = 11.237, $p < 0.001$) and teachers (β = −0.677, t = 13.704, $p < 0.001$). Hence, hypotheses H12 and H2 are supported. Lastly, de-humanization significantly correlates with development of students' socioemotional skills (β = 0.331, t = 7.781, $p < 0.001$). Hence, the hypothesized relationship H10 is supported ****(Figs. 10 and 11).

Table 17 provides a comprehensive overview of all hypothesis testing results. Overall, 9 out of 12 hypotheses (75%) were supported by the data. The three non-supported hypotheses include: (1) H4, the direct relationship between skills development and well-being at the higher-order construct level, which approached but did not reach statistical significance (p=0.058); (2) H8, the relationship between AIED and socioemotional skills (p=0.102); and (3) H9, the relationship between AIED and collaborative skills (p=0.258). Notably, while AIED did not directly affect non-cognitive skills, dehumanization significantly affect socio-emotional skill development (H10: β=0.331, $p< 0.001$), suggesting that more humanizing educational environments characterized by empathy, support, belonging, and human interaction are critical for fostering these competencies. All hypotheses related to the dehumanization and well-being pathway were strongly supported across both student and instructor samples, with instructors consistently showing stronger effect sizes.

Table 10 Discriminant validity—fornell-larcker criterion—students

		1	2	3	4	5	6	7	8	9	10	11	12	13
1	AIED adoption	0.774												
2	AIED scope	0.117	0.891											
3	Anxiety and depression	−0.174	−0.444	0.835										
4	Collaborative skills	0.157	−0.141	0.009	0.795									
5	Creative skills	0.226	−0.014	−0.217	0.507	0.868								
6	Critical skills	0.292	0.046	−0.222	0.603	0.566	0.767							
7	Empathy	0.243	0.224	−0.292	0.183	0.286	0.325	0.853						
8	Human interaction	0.236	0.207	−0.118	0.193	0.136	0.213	0.447	0.796					
9	Isolation and loneliness	−0.063	−0.231	0.2	−0.503	−0.344	−0.42	−0.341	−0.196	0.824				
10	Sense of belonging	0.261	0.329	−0.372	0.198	0.25	0.317	0.438	0.512	−0.278	0.829			
11	Socioemotional skills	0.258	−0.032	−0.307	0.5	0.514	0.639	0.348	0.231	−0.193	0.283	0.774		
12	Support	0.321	0.262	−0.242	0.261	0.219	0.259	0.532	0.487	−0.323	0.507	0.327	0.766	
13	Technical skills	0.245	−0.045	−0.064	0.623	0.553	0.679	0.32	0.194	−0.49	0.266	0.542	0.289	0.772

- Summary of Key Differences Between Student and Instructor Models Table 18 reveals both convergent and divergent patterns across stakeholder groups. Both students and instructors show significant positive AIED-dehumanization relationships (Students: $\beta = 0.434$, $p < 0.001$; Instructors: $\beta = 0.472$, $p < 0.001$). However, critical differences emerge: instructors demonstrate substantially stronger dehumanization-well-being effects ($\beta = -0.701$, $p < 0.001$) compared to students ($\beta = -0.251$, $p < 0.001$; ratio = 2.79×). This heightened vulnerability is also evident in the AIED→ Dehumanization→Well-Being mediation ($\beta = -0.331$ vs. $\beta = -0.114$) and isolation/loneliness components ($\beta = -0.677$ vs. $\beta = -0.363$, ratio = 1.86×). For students, AIED significantly enhances cognitive skills (critical: $\beta = 0.277$; technical: $\beta = 0.229$; creative: $\beta = 0.209$; all $p < 0.001$) but shows no direct effect on non-cognitive skills (socioemotional: $p = 0.102$; collaborative: $p = 0.258$). In particular, dehumanization predicts the development of socio-emotional skills ($\beta = 0.331$, $p < 0.001$), highlighting the importance of humanizing educational environments. Most importantly, Table 18 provides strong evidence of mediation effects. The indirect pathways demonstrate that dehumanization functions as a key mediating mechanism through which AIED influences both skills and well-being. Specifically, for students, the indirect effect of AIED on skills through dehumanization is positive and significant ($\beta = 0.166$, $p < 0.001$), while the indirect effect of AIED on well-being through dehumanization is negative and significant ($\beta = -0.114$, $p = 0.001$). For instructors, a similarly strong indirect effect is observed for the AIED $\rightarrow$ Dehumanization $\rightarrow$ Well-being pathway ($\beta = -0.331$, $p < 0.001$). These patterns have policy implications. Instructors need stronger psychological support. Students need balanced use of AI that preserves human interaction while supporting learning.

6 Discussion

This section discusses the main findings in relation to the study's aims and conceptual framework, offering insights into how AI is perceived to affect key human aspects of the educational experience. To ensure a focused and coherent interpretation, the discussion is structured around four interrelated subsections,each addressing a distinct yet connected dimension as revealed through the data.

6.1 Understanding dehumanization in AI-driven context

This study examined whether AI in education follows the dehumanization concerns discussed in the literature [128, 166] (Sect. 2.2). This study measured dehumanization through positively worded indicators such as support, empathy, belonging and human interaction(Fig. 2), where higher scores represent lower perceived dehumanization, while lower scores indicate a higher perceived dehumanization in the educational environment.Results revealed a significant positive relationship between generative AI use and perceived dehumanization for both students (β = 0.417, p < 0.001)and instructors (β = 0.472, p < 0.001) (Table 15).These finding suggest that greater engagement with generative AI tools is associated with higher level of perceived empathy,support, belonging and human interaction, reflecting a mitigation dehumanizing effect. This finding align with recent studies positioning generative AI as a potentially supportive layer in educational environments for both student and instructor when used purposefully [1, 69, 129, 138].

Table 11 Discriminant validity—fornell-larcker criterion—teachers

		1	2	3	4	5	6	7	8
1	AIED adoption	0.864							
2	AIED scope	0.768	0.89						
3	Anxiety and depression	−0.324	−0.297	0.89					
4	Empathy	0.313	0.288	−0.224	0.871				
5	Human interaction	0.314	0.243	−0.294	0.369	0.792			
6	Isolation and loneliness	−0.373	−0.318	0.357	−0.35	−0.419	0.882		
7	Sense of belonging	0.425	0.371	−0.365	0.348	0.508	−0.588	0.879	
8	Support	0.381	0.347	−0.376	0.464	0.434	−0.617	0.597	0.834

Table 12 Collinearity assessment

HOC	LOC	Students	Teachers
		VIF	
AI in education	LV scores—adoption	1.016	2.264
	LV scores—scope	1.016	2.264
De-humanization	LV scores—empathy	1.506	1.346
	LV scores—human interaction	1.608	1.454
	LV scores—sense of belonging	1.648	1.746
	LV scores—Support	1.666	1.788
Skills development	LV scores—critical skills	2.532	N/A
	LV scores—technical skills	2.210	N/A
	LV scores—creative skills	1.696	N/A
	LV scores—socioemotional skills	1.829	N/A
	LV scores—collaborative skills	1.933	N/A
Well-Being	LV scores—isolation and loneliness	1.112	1.147
	LV scores—anxiety and depression	1.112	1.147

Table 13 Significance of weights

HOC	LOC	Outer weights					
		Original sample	*t* values	*p* value	Original sample	*t* values	*p* value
		Students			Teachers		
AI in education	LV scores—adoption	0.840***	8.053***	< 0.001	0.586***	3.197***	0.001
	LV scores—scope	0.449**	3.117**	0.002	0.483**	2.642**	0.008
De-humanization	LV scores—empathy	0.511***	4.912***	< 0.001	0.116	1.626	0.104
	LV scores—human interaction	−0.065	0.742	0.458	0.122	1.39	0.165
	LV scores—sense of belonging	0.461***	4.931***	< 0.001	0.489***	4.162***	< 0.001
	LV scores—support	0.298**	2.811**	0.005	0.485***	3.998***	< 0.001
Skills development	LV scores—critical skills	0.327*	2.195*	0.028	N/A	N/A	N/A
	LV scores—technical skills	0.364**	2.72**	0.007	N/A	N/A	N/A
	LV scores—creative skills	0.251	1.844	0.065	N/A	N/A	N/A
	LV scores—socioemotional skills	0.268	0.917	0.359	N/A	N/A	N/A
	LV scores—collaborative skills	−0.010	0.035	0.972	N/A	N/A	N/A
Well-being	LV scores—Isolation and loneliness	0.736***	4.426***	< 0.001	0.384***	4.952***	< 0.001
	LV scores—anxiety and depression	0.483	1.546	0.122	0.796***	13.183***	< 0.001

Table 14 Significance of outer loadings

HOC	LOC	Outer weights					
		Original Sample	t values	p value	Original sample	t values	p value
		Students			Teachers		
AI in education	LV scores—adoption	0.687***	7.329***	< 0.001	0.947***	19.565***	< 0.001
	LV scores—scope	0.646***	6.969***	< 0.001	0.921***	19.228***	< 0.001
De-humanization	LV scores—empathy	0.847***	16.538***	< 0.001	0.561***	7.109***	< 0.001
	LV scores—Human interaction	0.56***	8.015***	< 0.001	0.626***	6.665***	< 0.001
	LV scores—Sense of belonging	0.812***	19.112***	< 0.001	0.879***	16.356***	< 0.001
	LV scores— support	0.767***	12.46***	< 0.001	0.883***	16.912***	< 0.001
Skills development	LV scores—critical skills	0.88***	9.633***	< 0.001	N/A	N/A	N/A
	LV scores—technical skills	0.86***	12.969***	< 0.001	N/A	N/A	N/A
	LV scores—creative skills	0.767***	7.233***	< 0.001	N/A	N/A	N/A
	LV scores—socioemotional skills	0.796***	4.103***	< 0.001	N/A	N/A	N/A
	LV scores—collaborative skills	0.684***	5.632***	< 0.001	N/A	N/A	N/A
Well-being	LV scores—isolation & Loneliness	0.889***	10.203***	< 0.001	0.669***	8.919***	< 0.001
	LV scores—anxiety and depression	0.716**	2.607**	0.009	0.934***	31.833***	< 0.001

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

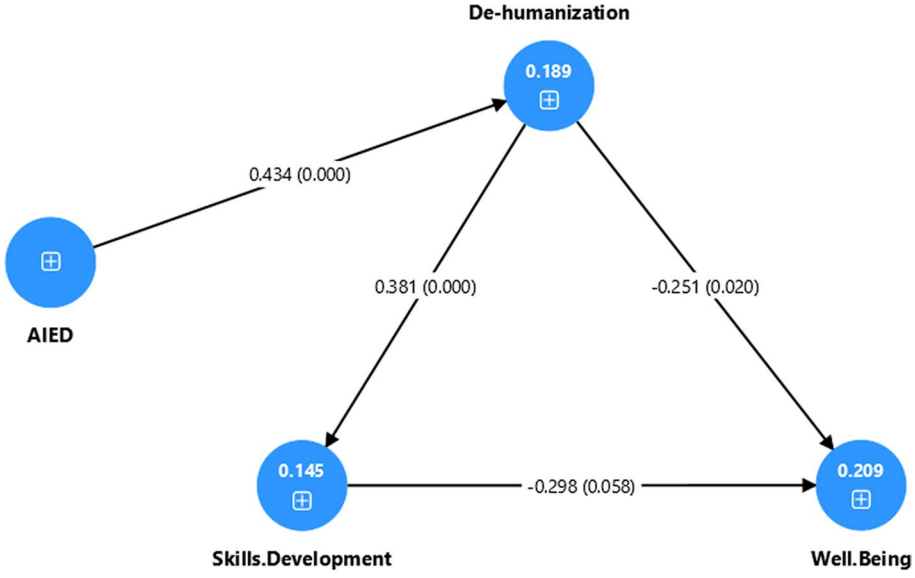


Fig. 8 Assessment of higher-order construct and path analysis—students

While these findings contrasts with dominant critiques of AI's dehumanizing potential, it does not negate the broader risks outlined in the literature [43, 70]. Although AI is increasingly positioned as a transformative force in education, it is not immune to concerns about its unintended social and emotional consequences.

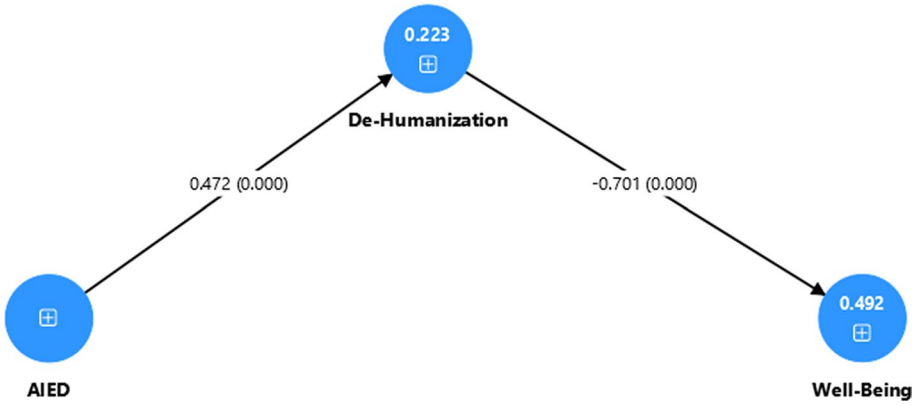


Fig. 9 Assessment of higher-order construct and path analysis—instructor/teachers model

The promises of AI implementation exist alongside widespread worries about its potential to create dehumanizing learning experience [43, 93, 157, 166]. The over-reliance on AI tools creates concerns of reducing the essential emotional and relational aspects of human learning particularly belonging and empathy, support and human interaction [79, 192]. Students who spend more time interacting with technology instead of peers and educators may experience diminished opportunities for recognition along with care and inclusion [43, 70]. Many recent studies still emphasizes that dehumanization can still arise from the absence of meaningful human presence within AI-supported educational environments [43, 70]. Emerging literature has begun to explore the possibility that AI use may influence how individuals perceive themselves and others, potentially introducing subtle dehumanizing effects [43].

Thus, while the current findings do not indicate a direct rise in perceived dehumanization, these concerns highlight the importance of continuous monitoring [166] and should be interpreted cautiously. The positive associations observed may reflect early-stage perceptions or context-specific implementations where AI genuinely enhances rather than replaces human connection. Continuous monitoring remains essential to ensure AI tools are implemented in ways that preserve empathy, inclusion, and human connection [166]. Future research should examine longitudinal effects and explore whether initial positive perceptions persist as AI integration deepens. Ensuring that AI tools are implemented in ways that preserve empathy, inclusion, and human connection remains essential in educational settings.

6.2 The shadow of skill decay in student learning

The research demonstrates that AIED has a strong positive impact on the development of multiple skills including critical skills ($p < 0.001$), technical skills ($p < 0.001$), and creative skills ($p < 0.001$) among students (Table 17). These findings align with the existing literature that highlights the role of AI in the development of cognitive abilities, especially analytical reasoning and technical skills [5, 52, 117, 195]. On the other hand, the relationships between AIED socio-emotional skills ($p = 0.102$) and collaborative skills ($p = 0.258$) were not statistically supported in this study (Table 17). This outcome is aligned with concerns in prior studies that question AI's

Table 15 Results from PLS-SEM analysis—main hypotheses

Hypothesis	Students				Teachers				
	Original sample (O)	Standard deviation (STDEV)	t statistics (|O/STDEV|)	p values	Original sample (O)	Standard deviation (STDEV)	t statistics (|O/STDEV|)	p values	Decision
AIED → De-Humanization	0.434***	0.034	12.598***	< 0.001	0.472***	0.076	6.237***	< 0.001	Supported
De-humanization → Skills Development	0.381***	0.098	3.895***	< 0.001	N/A	N/A	N/A	N/A	Supported
De-humanization → Well-Being	−0.251***	0.108	2.325***	0.020	−0.701***	0.046	15.146***	< 0.001	Supported
Skills development → Well-Being	−0.350	0.157	1.893	0.058	N/A	N/A	N/A	N/A	Not Supported

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

ability to foster emotional regulation, and teamwork spirut [5, 22, 99]. These particular results areas emphasized the need for deeper investigation, as they are mainly developed through genuine human interaction settings, which AI still cannot fully replicate.

On the bright side, this study's findings demonstrate that AI can support a wide range of skills but requires proper implementation methods. For instance, as supported in the literature that AI improves technical skills through coding and data analysis, and information retrieval [98, 121], yet many worries about its impact on other skills. The use of AIED systems could reduce opportunities for meaningful human interaction, which would negatively affect students' socio-emotional development [43]. The learning process becomes harder to duplicate through automated systems because AI systems diminish empathy and decrease feelings of belonging and emotional support [70, 166].

Despite the perceived benefits, the increased use of AI tools creates a critical issue which is excessive overreliance [9, 91]. Students who heavily use AI tools to generate ideas and solve problems tend to reduce their own skills in the learning process [9, 91, 198]. The excessive use results in a progressive deterioration of fundamental abilities, which has been widely discussed in the literature as skill decay [32, 111, 198]. Students who depend heavily on AI without critical thinking face an increased risk of damaging their reasoning abilities,creativity, and design making [111, 198].The solution lies in finding balance between AI support and skill development to allow technology to boost fundamental learning activities instead of replacing them.

As we discuss skill development, some research notes that a dehumanized environment can adversely affect socio-emotional skills. For example, spaces with low interaction or emotional presence are seen to weaken the development of important interpersonal skills [29, 41]. These worries drawn from the literature, urge testing this relationship (R10). our result (Table) is that participants with lower perceived dehumanization are more likely to enhance their socio-emotional skills (β = 0.331, p < 0.001). As a result, when participants are exposed to a higher level of human-based interaction in their space, socio-emotional skills are strengthened, not diminished, in line with prior research emphasizing the buffering effect of connectedness in skill development [24, 29].

6.3 The connection between human presence and well-being among students and instructors

The results indicate that students and instructors who reported higher perceptions of belonging, support, empathy, and meaningful human interaction were significantly less likely to experience symptoms of anxiety and depression (β = −0.340, p < 0.001), or social isolation and loneliness (β = −0.363, p < 0.001). Theoretical perspectives on dehumanization suggest that when individuals feel a lack of belonging, emotional support, empathy, or meaningful human interaction, the psychological toll can be substantial [71, 86]. These factors are not just socially ideals but also foundational to better well-being. Based on that, the results show that greater participant perceived human presence in educational settings is significantly associated with lower levels of psychological distress [83, 104, 114].

Table 16 Results from PLS-SEM analysis—special indirect effects (main hypotheses)

Hypothesis	Students				Teachers				
	Original sample (O)	Standard deviation (STDEV)	t statistics (|O/STDEV|)	p values	Original sample (O)	Standard deviation (STDEV)	t statistics (|O/STDEV|)	p values	Decision
AIED → De-humanization → Skills Development	0.166***	0.045	3.689***	< 0.001	N/A	N/A	N/A	N/A	Supported
De-humanization → Skills development → Well-Being	–0.109	0.048	2.262	0.024	N/A	N/A	N/A	N/A	Not Supported
AIED → De-humanization → Well-Being	–0114***	0.030	3.816***	0.001	–0.331***	0.066	5.030***	< 0.001	Supported
De-humanization → Skills Development → Well-Being	–0.049**	0.014	3.413**	< 0.001	N/A	N/A	N/A	N/A	Supported

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

Given that our study focus on AI in education and the risk associate with it including well-being [43],a mediation analysis was conducted to explore whether AIED influences well-being through its effect on the dehumanization block factors. The results show that AIED can indirectly decrease the level of anxiety, depression and loneliness when humanizing elements such as empathy, support, and a sense of belonging are increased and preserved within the learning environment ($\beta = -0.122$, $p < 0.001$). These findings in align with previous studies [148, 155] which indicates that AI systems should combine pedagogical effectiveness with social and emotional aspect during their design process. AI-enabled systems should be used as constructive instruments to maintain essential human experiences in the educational settings.

6.4 Toward socially responsible AIED

The rapid integration of AI into educational systems has made socially responsible AIED a matter of growing urgency [24, 33]. Socially responsible AIED aims to balance rapid technological innovations with human-centered values, implementing AI in ways that benefit society while reducing the risks involved [8, 33]. The the inclusion of social aspect describes that ethical AI that does not serve purely as an efficient mechanism, but rather a power to be shielded with equity, responsibility, and social well-being [33]. To establish socially responsible AIED, it is essential to understand how AI affects the educational experience holistically, particularly through its influence on dehumanization, well-being, and skill development. Dehumanization as a major concern demonstrates the extent to which educational stakeholders feel disconnected, unsupported through technology driven- experiences like AI [33, 112]. Well-being encompasses the need to maintain psychological and emotional health in light of increasing AI use [145, 185, 186]. Skill development captures the need to balance between AI assistance and excessive overreliance that might negatively affect students' cognitive and non-cognitive skill growth [52]. The assessment of AI impacts on human experience requires examination of these interconnected constructs as a whole. For instance, by looking at the indirect effect, findings demonstrate that lower levels of perceived dehumanization are associated with better emotional and social connections among students while also preserving their socioemotional development abilities. The research demonstrates that AI benefits certain learning areas but its negative effects on well-being urgently required careful policy design to preserve and maintain the overall psychological and emotional health for both student and instructors [107, 163].

Although, empirical insights derived from this study shows the perceptions around AIED and crucial social relevant aspect, a comprehensive understanding necessitates awareness of organizational factors that also critically influence the AI adoption in the educational environment [14, 18, 33]. As part of the future work, these factors will be explored qualitatively through interviews with decision-makers and senior stakeholders in the education sector, who are responsible for fostering environments that support ethical and effective AI integration. While this paper does not provide an in-depth analysis of these factors, brief descriptions are included to highlight their relevance in achieving socially responsible and sustainable AI adoption within educational contexts.

Table 17 Summary of all hypotheses testing results

H#	Hypothesis	Sample	β	p	Decision
Main structural hypotheses					
H1	AIED → Dehumanization	Students	0.434	<0.001	✓ **Supported**
		Instructors	0.472	<0.001	✓ **Supported**
H2	Dehumanization → Skills	Students	0.381	<0.001	✓ **Supported**
		Instructors			
H3	Dehumanization → Well-Being	Students	−0.251	0.020	✓ **Supported**
		Instructors	−0.701	<0.001	✓ **Supported**
H4	Skills → Well-Being	Students	−0.350	0.058	× **Not Supported**
		Instructors			
Factor-level: AIED effects on skills					
H5	AIED → Critical Skills	Students	0.277	<0.001	✓ **Supported**
H6	AIED → Technical Skills	Students	0.229	<0.001	✓ **Supported**
H7	AIED → Creative Skills	Students	0.209	<0.001	✓ **Supported**
H8	AIED → Socioemotional Skills	Students	0.119	0.102	× **Not Supported**
H9	AIED → Collaborative Skills	Students	0.141	0.258	× **Not Supported**
Factor-level: dehumanization effects					
H10	Dehumanization. → Socioemotional Skills	Students	0.331	<0.001	✓ **Supported**
H11	Dehumanization. → Anxiety & Depression	Students	−0.340	<0.001	✓ **Supported**
		Instructors	−0.421	<0.001	✓ **Supported**
H12	Dehumanization. → Isolation & Loneliness	Students	−0.363	<0.001	✓ **Supported**
		Instructors	−0.677	<0.001	✓ **Supported**

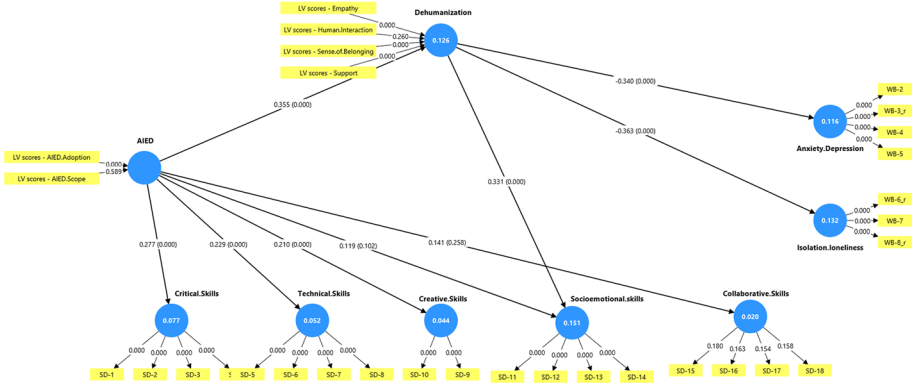


Fig. 10 Assessment of factor level analysis and path analysis—student model

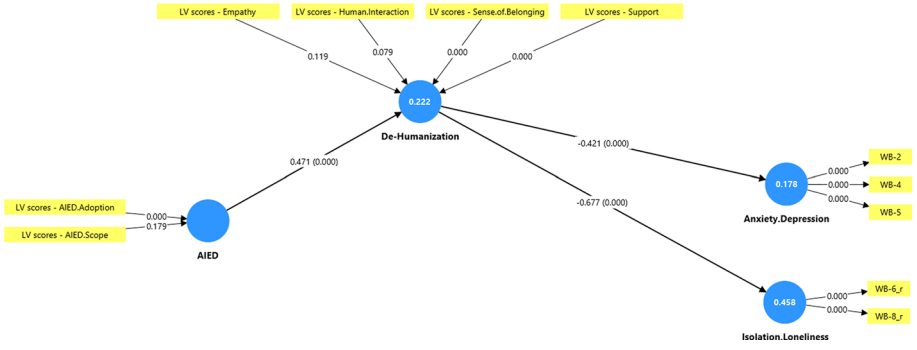


Fig. 11 Assessment of factor level analysis and path analysis—instructors/teachers model

Table 18 Comparison of path coefficients: student versus instructor models

	Student model (N=764)			Instructor model (N=235)		
Hypothesized path	β	***t***	***p***	β	***t***	***p***
Main structural paths (higher-order constructs)						
H1: AIED → Dehumanization	0.434***	12.598	<0.001	0.472***	6.237	<0.001
H2: Dehum. → Skills Development	0.381***	3.895	<0.001	N/A		
H3: Dehum. → Well-Being	−0.251**	2.325	0.020	−0.701***	15.146	<0.001
H4: Skills → Well-Being	−0.350	1.893	0.058	N/A		
Indirect effects (mediation pathways)						
AIED → Dehum. → Skills	0.166***	3.689	<0.001	N/A		
AIED → Dehum. → WB	−0.114***	3.816	0.001	−0.331***	5.030	<0.001
Dehum. → Skills → WB	−0.109*	2.262	0.024	N/A		
Factor-level: AIED → skill types (students only)						
H5: AIED → critical skills	0.277***	6.687	<0.001	N/A		
H6: AIED → technical skills	0.229***	3.752	<0.001	N/A		
H7: AIED → creative skills	0.209***	3.960	<0.001	N/A		
H8: AIED → socioemotional skills	0.119	1.636	0.102	N/A		
H9: AIED → collaborative skills	0.141	1.132	0.258	N/A		
Factor-level: dehumanization → well-being components						
H11: Dehum. → Anxiety & Depression	−0.340***	11.940	<0.001	−0.421***	6.257	<0.001
H12: Dehum. → Isolation & Loneliness	−0.363***	11.237	<0.001	−0.677***	13.704	<0.001
Factor-level: other paths (students only)						
H10: Dehum. → Socioemotional Skills	0.331***	7.781	<0.001	N/A		

This study provides a comprehensive understanding of socially responsible AIED by synthesizing findings from the conceptual model while also acknowledging the importance of organizational-level factors. Crucially, this approach supports Sustainable Development Goal 4 (SDG 4) because it contributes to promoting inclusive quality education and lifelong learning opportunities for all [154]. The implementation of socially responsible AI design, which maintains human connection directly helps achieve SDG 4 by improving student capabilities for lifelong learning and overall well-being. Additionally, the research shifts the discussion beyond traditional efficiency and performance metrics, emphasizing the importance of learners' emotional experiences, social connections, and developmental growth in AI-mediated settings.

7 Limitations and future research

The research provides valuable insight on the perceived dehumanization, well-being, and skill development in the age of AI, however, it has multiple limitations that present an opportunity for future exploration:

Although this model includes major social factors of skill development, well-being, and dehumanization, it does not cover all relevant factors comprehensively. More context-embedded factors such as institutional reputations, academic integrity, and perceptions of control and autonomy of AI-improved learning spaces may complement this model in future studies. In addition, including factors such as physical well-being may also provide a better and more comprehensive picture of how AI affects individual and shared experiences in higher education.

Another significant limitation resides in the data sources utilized. Self-reporting data provides valuable insights through participant perceptions yet it contains several notable limitations. Participants might give inaccurate information because they want to appear

more socially acceptable or because they find it hard to remember their actual behaviors [3, 101]. Though these insights afford richness and real-lived experience, a future study could enhance validity by coupling them with more objective measures like performance data, fine-grained analytics on student engagement, or longer-term tracking of learning outcomes [177]. Such triangulation would permit a more balanced and comprehensive understanding [72].

Moreover, the study focuses exclusively on specific cultural and institutional environments of Saudi Arabia. As such, the generalizability of the findings to other educational systems or sociocultural contexts may be limited [51]. The unique socio-political dynamics, educational policies, and cultural attitudes toward technology in Saudi Arabia may differ significantly from those of other regions. Future research could benefit from comparative studies across diverse educational and cultural landscapes to enhance the applicability and relevance of the findings. Additionally, The sample was predominantly female (59.4%), reflecting current enrollment patterns in Saudi higher education [57]. While this distribution aligns with national participation trends, future research may build on these findings by examining gender-balanced samples across different regions to explore whether similar patterns emerge in alternative institutional and cultural contexts.

lastly, the absence of qualitative data prevents a holistic and deeper understanding of the detailed contextual reasons behind participant perceptions [82]. Without open-ended input, the study cannot fully capture the nuanced motivations driving participants' responses. Future research needs to incorporate qualitative or mixed-method approaches to gather more detailed contextual information, which would enhance the model's applicability in different educational environments.

Despite these limitations, this study establishes a critical foundation for further research and policy development by highlighting dimensions that are often overlooked in an efficiency-driven society [10]. By prioritizing the nuanced aspects of dehumanization, well-being, and skill development, the study shifts the focus to the broader human-centric implications of AI in higher education.

8 Conclusions

This study significantly advances the understanding of AI in education by shifting focus from mere efficiency to its profound social implications. AI offers opportunities as well as challenges for developing a holistic, human-centered learning environment. As it has the potential for improving academic efficiency, productivity and personalizing learning experiences, there is a need for careful consideration of possible social concerns, including dehumanization, the changing nature of skill development, as well as well-being. The study finding suggests call for a balanced approach where AI is utilized for improving social-technical aspect of educational environment. Ultimately, the goal is to provide insights for policymakers to formulate a humanistic, sustainable and socially responsible adoption strategy, ensuring that AI enhance learning outcomes, support ethical standards, foster skill development, and promote educational stakeholder's well-being.

Appendix A: Survey instrument

Table 19 Survey questions

Factor	Subfactor	Question code	Survey question	References
AI in education (AIED)	Adoption	AIED 1	I am familiar with AI tools like ChatGPT	
		AIED 2	I frequently use AI tools like ChatGPT in my work/study	[63, 84, 187]
		AIED 3	I use AI tools for personal learning (outside of formal education/work)	
	Scope	AIED 4	I find generative AI tools are useful for my work/study	
		AIED 5	I think using AI tools improves my productivity	[59, 63, 84]
		AIED 6	I find that AI tools enhance the quality of my work	
		AIED 7	I think the use of generative AI may undermine the credibility or integrity of my work	
		AIED 8	I think that over-reliance on generative AI may decrease my ability to critically assess my work	
		AIED 9	I think the use of AI may introduce bias into my work	
Skill development	Critical skills	SD 1	I usually seek additional information when I do not understand something	
		SD 2	I am usually considering multiple perspectives while making decisions	[52, 172]
		SD 3	I think about the possible wider implications while making decisions	
		SD 4	I usually evaluate the credibility and value of information presented to me	
	Technical skills	SD 5	I am able to apply technical knowledge to solve practical problems	
		SD 6	I am able to learn and adapt to new technology	[98, 125]
		SD 7	I am able to stay up to date with the latest technology	
		SD 8	I am able to apply reverse engineering (analysing an existing solution and applying it to solve a different problem)	
	Creative	SD 9	I am able to come up with innovative ideas or solutions	[97, 142]
		SD 10	I enjoy finding novel/unique ways to develop my work	
	Socio-emotional	SD 11	I manage my emotions when facing difficulties	
		SD 12	I am able to form positive and meaningful relationships with others	[200, 203]
		SD 13	I understand how others (e.g., peers) are feeling in different situations	
		SD 14	I am able to recognize my strengths and weaknesses and improve accordingly	
	Collaborative	SD 15	I enjoy collaborating with others	
		SD 16	I am open to ideas and suggestions from other team members	[40, 75]
		SD 17	I believe that the success of my team depends on the active participation of all members	
		SD 18	I make efforts to build a positive atmosphere within my team	

Table 19 (continued)

Factor	Subfactor	Question code	Survey question	References
De-humanization	Sense of belonging	DH 1	I feel connected to my work/study environment	
		DH 2	I feel that my efforts and input are recognized in my work/study environment	[56, 116]
	Human interaction	DH 3	I believe I have enough face-to-face interaction with others in my environment	
		DH 4	I feel that my communication with others in my environment is genuine and meaningful	[174]
		DH 5	Social interaction is important to me within an educational environment	
	Support	DH 6	I feel supported by people in my work/study setting	
		DH 7	I feel that people in my educational environment understand my feelings	[130]
		DH 8	I rely on people in my educational environment	
	Empathy	DH 9	I am able to understand others' feelings	[115]
		DH 10	I am open to talking with others about potentially sensitive matters in my educational environment	
Well-being	Anxiety and depression	WB 1	I am normally concerned or scared without any actual reason	[122, 131]
		WB 2	I tend to avoid certain places or situations to prevent uncomfortable feelings	
		WB 3	I am able to control myself when I am concerned or scared	
		WB 4	I feel I am not enthusiastic enough about daily activities	
	Isolation and loneliness	WB 5	I feel I don't have enough positive feelings	
		WB 6	I am happy with my social relationships	[136]
		WB 7	I feel the need to isolate myself from others	
		WB 8	I feel that people around me are available when I need them	

Appendix B: Supplementary figures and statistics

See Table 21.

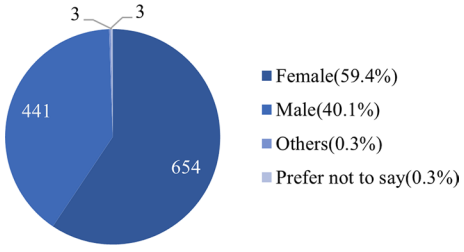


Fig. 12 Gender distribution

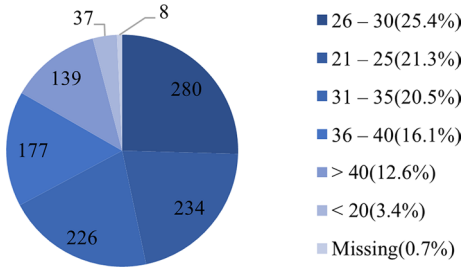


Fig. 13 Age distribution by role

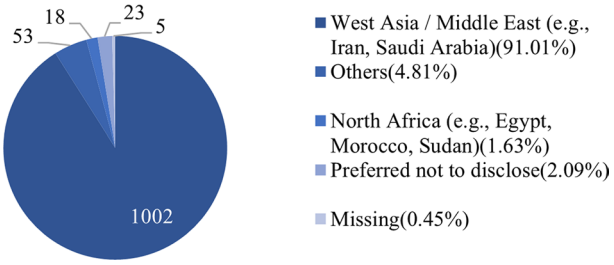


Fig. 14 Ethnic origins or ancestry

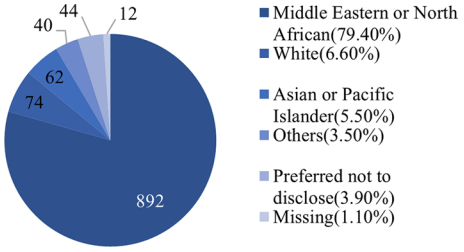


Fig. 15 Race distribution

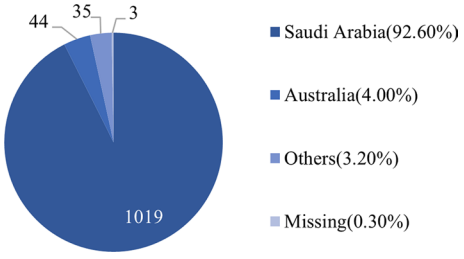


Fig. 16 Country of working/studying

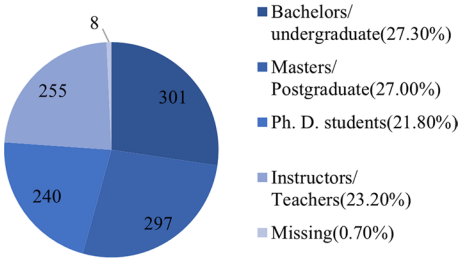


Fig. 17 Current occupation

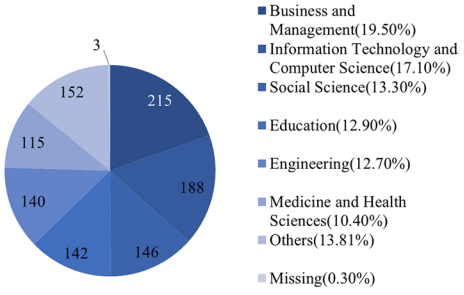


Fig. 18 Field of study/department

Table 20 Descriptive statistics and normality

	Mean	SD	Skewness	Kurtosis
AI in education				
AIED 1	4.24	0.912	−1.538	2.770
AIED 2	4.02	0.907	−1.144	1.692
AIED 3	4.06	0.873	−1.181	1.972
AIED 4	4.19	0.862	−1.230	1.878
AIED 5	4.21	0.8–68	−1.328	2.133
AIED 6	4.23	0.825	−1.337	2.573
AIED 7	2.49	1.224	0.668	−0.554
AIED 8	2.57	1.246	0.576	−0.755
AIED 9	2.37	1.261	0.659	−0.640
Skills development				
SD 1	4.44	0.903	−1.809	3.041
SD 2	4.03	0.756	−1.019	2.300
SD 3	3.95	0.854	−0.867	1.079
SD 4	4.20	0.874	−1.271	1.948
SD 5	4.06	0.879	−1.148	1.737
SD 6	4.14	0.818	−1.110	1.806
SD 7	4.15	0.878	−1.057	1.072
SD 8	3.91	0.964	−0.894	0.655
SD 9	4.02	0.840	−0.769	0.651
SD 10	4.10	0.866	−0.927	0.818
SD 11	4.11	0.843	−0.865	0.511
SD 12	4.13	0.889	−0.861	0.213
SD 13	3.97	0.804	−0.591	0.349
SD 14	3.98	0.912	−0.762	0.239
SD 15	4.10	0.938	−1.387	2.285
SD 16	4.20	0.895	−1.628	3.553
SD 17	4.21	0.905	−1.709	3.763
SD 18	4.08	0.919	−1.287	2.092
De-humanization				
DH 1	4.27	0.892	−1.404	2.100
DH 2	3.93	0.919	−1.108	1.451
DH 3	3.98	0.836	−1.002	1.523
DH 4	4.31	0.871	−1.412	2.085
DH 5	4.28	0.808	−1.327	2.356
DH 6	4.12	0.830	−0.961	1.166
DH 7	4.00	0.944	−0.805	0.293
DH 8	3.84	0.945	−0.830	0.491
DH 9	4.11	0.865	−1.287	2.418
DH 10	3.95	0.958	−1.175	1.476
Well-being				
WB 1	3.55	1.411	−0.531	−1.087
WB 2	2.66	1.348	0.481	−1.042
WB 3	3.70	1.078	−1.032	0.577
WB 4	2.39	1.298	0.523	−0.955
WB 5	2.43	1.265	0.669	−0.711
WB 6	4.13	1.030	−1.393	1.562
WB 7	2.45	1.244	0.704	−0.523
WB 8	3.86	1.018	−1.061	0.911

Table 21 Collinearity assessment- for lower order constructor (LOC)

	VIF—students	VIF—teachers
AIED1	1.463	1.744
AIED2	1.800	2.568
AIED3	1.518	2.503
AIED4	1.696	2.665
AIED5	1.699	2.449
AIED6	1.600	2.628
DH1	1.212	1.431
DH2	1.212	1.431
DH3	1.359	1.342
DH4	1.529	1.466
DH5	1.400	1.353
DH6	1.275	1.783
DH7	1.420	1.742
DH8	1.277	1.460
DH9	1.262	1.370
DH10	1.262	1.370
SD1	1.641	N/A
SD2	1.454	N/A
SD3	1.519	N/A
SD4	1.514	N/A
SD5	1.687	N/A
SD6	1.388	N/A
SD7	1.459	N/A
SD8	1.617	N/A
SD9	1.347	N/A
SD10	1.347	N/A
SD11	1.583	N/A
SD12	1.437	N/A
SD13	1.591	N/A
SD14	1.527	N/A
SD15	1.723	N/A
SD16	1.502	N/A
SD17	1.774	N/A
SD18	1.788	N/A
WB2	2.708	1.881
WB3	1.321	N/A
WB4	2.632	2.951
WB5	2.799	2.668
WB6	1.707	1.448
WB7	1.374	N/A
WB8	1.727	1.448

Acknowledgements
The author would like to thank all participants and respondents who contributed to this study. The author would also like to thank Dr. Salvatore Flavio Pileggi and Dr. Faezeh Karimi for their invaluable guidance, feedback, and encouragement throughout the course of this research.

Author contributions
All authors contributed to the study's conceptualization and methodology. The manuscript was written by Budur Turki Alshahrani. Supervision and review were provided by Dr. Salvatore Flavio Pileggi and Dr. Faezeh Karimi. All authors have approved the final version of the manuscript.

Funding
No funding was received for conducting this study.

Data availability
The data and materials supporting the findings of this study are publicly available at https://doi.org/10.5281/zenodo.15347028.

Declarations

Ethics approval and consent to participate
The study received ethical approval from the University of Technology Sydney (UTS HREC REF NO. ETH24-9930). Consent was obtained from all participants prior to participation in the study, and all procedures were carried out in strict accordance with the UTS Human Research Ethics guidelines to protect confidentiality, data security and no identifiable information is reported. Participation was voluntary. Each participant received an information sheet and gave informed consent prior to participation.

Consent for publication
Not applicable.

Competing interests
The authors declare that they have no competing interests.

Received: 10 September 2025 / Accepted: 3 April 2026
Published online: 19 April 2026

References

1. Aberšek, B, Flogie, A, Aberšek MK. Transformation of education: from dehumanization to re-humanization of society. In International baltic symposium on science and technology education. Scientia Socialis Ltd., Šiauliai, Lithuania, 2023. https://doi.org/10.33225/jbse/23.22.XXX.
2. Acione PAF. The disposition toward critical thinking: its character, measurement, and relationship to critical thinking skill. Technical report.
3. Adolphs R, Nummenmaa L, Todorov A, Haxby JV. Data-driven approaches in the investigation of social perception. Philos Trans R Soc B Biol Sci. 2016;371(1693):20150367.
4. AIPRM. Ai in education statistics. https://www.aiprm.com/ai-in-education-statistics/, 2024. Accessed 22 Jul 2025.
5. Akintayo OT, Eden CA, Ayeni OO, Onyebuchi NC. Integrating AI with emotional and social learning in primary education: developing a holistic adaptive learning ecosystem. Comput Sci IT Res J. 2024;5(5):1076–89.
6. Al-Zahrani AM. Unveiling the shadows: beyond the hype of AI in education. Heliyon, 2024;10(9).
7. Al-Zahrani AM, Alasmari TM. Exploring the impact of artificial intelligence on higher education: the dynamics of ethical, social, and educational implications. Humanit Soc Sci Commun. 2024;11(1):1–12.
8. Aler Tubella A, Mora-Cantallops M, Nieves JC. How to teach responsible AI in higher education: challenges and opportunities. Ethics Inf Technol. 2024;26(1):3.
9. Alshahrani BT, Pileggi SF, Karimi F. A social perspective on ai in the higher education system: a semisystematic literature review. Electronics. 2024;13(8):1572.
10. Amdan MAB, Janius N, Kasdiah MAHB, et al. Concept paper: efficiency of artificial intelligence (ai) tools for stem education in Malaysia. Int J Sci Res Arch. 2024;12(2):553–9.
11. An Y, Ji Hyun Yu, James S. Investigating the higher education institutions' guidelines and policies regarding the use of generative ai in teaching, learning, research, and administration. Int J Educ Technol High Educ. 2025;22(1):10.
12. Awang P, et al. SEM made simple: a gentle approach to learning structural equation modeling. Bangi: MPWS Rich Publication; 2015.
13. Baidoo-Anu D, Ansah LO. Education in the era of generative artificial intelligence (ai): understanding the potential benefits of chatgpt in promoting teaching and learning. J AI. 2023;7(1):52–62.
14. Balasubramaniam N, Kauppinen M, Kujala S, Hiekkanen K. Ethical guidelines for solving ethical issues and developing ai systems. In Product-Focused Software Process Improvement: 21st International Conference, PROFES 2020, Turin, Italy, November 25–27, 2020, Proceedings 21, pp. 331–346. Springer, 2020.
15. Baronchelli A. Shaping new norms for ai. Philos Trans R Soc B. 2024;379(1897):20230028.
16. Baumeister RF. Need-to-belong theory. Handbook of theories of social psychology. 2012;2:121–40.
17. Becker R. Gender and survey participation: An event history analysis of the gender effects of survey participation in a probability-based multi-wave panel study with a sequential mixed-mode design. Methods Data Analyses J Quantitative Method Survey Methodology (mda). 2022;16(1):3–32.
18. Bellamy R. Social readiness of adaptation technologies. Wiley Interdiscip Rev Clim Change. 2019;10(6):e623.
19. Bennett DA. How can i deal with missing data in my study? Aust N Z J Public Health. 2001;25(5):464–9.
20. Beuke CJ, Fischer R, McDowall J. Anxiety and depression: why and how to measure their separate effects. Clin Psychol Rev. 2003;23(6):831–48.
21. Boal MWE, Anastasiou D, Tesfai F, Ghamrawi W, Mazomenos E, Curtis N, et al. Evaluation of objective tools and artificial intelligence in robotic surgery technical skills assessment: a systematic review. Br J Surg. 2024;111(1):znad331.
22. Bond M, Khosravi H, De Laat M, Bergdahl N, Negrea V, Oxley E, et al. A meta systematic review of artificial intelligence in higher education: a call for increased ethics, collaboration, and rigour. Int J Educ Technol High Educ. 2024;21(1):4.
23. Boscardin CK, Gin B, Golde PB, Hauer KE. ChatGPT and Generative Artificial Intelligence for Medical Education: Potential Impact and Opportunity. Academic Medicine, 8 2023. ISSN 1040-2446. https://doi.org/10.1097/acm.0000000000005439.
24. Bosch N. Artificial intelligence, social responsibility, and the roles of the university, 2024. URL https://cacm.acm.org/opinion/artificial-intelligence-social-responsibility-and-the-roles-of-the-university/.
25. Brown TA. Confirmatory factor analysis for applied research. Guilford publications, 2015.
26. Brynjolfsson E, Rock D, Syverson C. Artificial intelligence and the modern productivity paradox. Econ Artif Intell Agenda. 2019;23(2019):23–57.
27. Buragohain D. A survey on digital immigrants' technology usage and practice in teaching digital natives. Int Res Edu. 2020;8(1):1–14. https://doi.org/10.5296/ire.v8i1.15560.
28. Cai Y, Yang Y, Ge Q, Weng H. The interplay between teacher empathy, students' sense of school belonging, and learning achievement. Eur J Psychol Educ. 2023;38(3):1167–83.

29. Camangian P, Cariaga S. Social and emotional learning is hegemonic miseducation: students deserve humanization instead. Race Ethn Educ. 2022;25(7):901–21.
30. Cambra-Fierro, JJ, Blasco MF, López-Pérez M-EE, Trifu A. Chatgpt adoption and its influence on faculty well-being: an empirical research in higher education. Edu Info Tech, pp. 1–22, 2024.
31. Candra S, Tulangow CE, Winalda FT. A preliminary study of consumer behavior from the online marketplace in Indonesia. Int J Asian Bus Inf Manag (IJABIM). 2022;13(1):1–17.
32. Carioli P, Czarnitzki D, Fernández GP. Evidence on the adoption of artificial intelligence: the role of skills shortage. ZEW Discussion Papers, 24, 2024.
33. Chang Y-L, Ke J. Socially responsible artificial intelligence empowered people analytics: a novel framework towards sustainability. Hum Resour Dev Rev. 2024;23(1):88–120.
34. Chen F. Human-ai cooperation in education: human in loop and teaching as leadership. J Edu Tech Inno, 2022;2(1).
35. Chen, Y-H, Rendina-Gobioff G, Dedrick RF. Detecting effects of positively and negatively worded items on a self-concept scale for third and sixth grade elementary students. Online submission, 2007.
36. Cheng L, Varshney KR, Liu H. Socially responsible ai algorithms: issues, purposes, and challenges. J Artif Intell Res. 2021;71:1137–81.
37. Chinta SV, Wang Z, Yin Z, Hoang N, Gonzalez M, Quy TL, Zhang W. Fairaied: Navigating fairness, bias, and ethics in educational ai applications. arXiv preprint arXiv:2407.18745, 2024.
38. Cho Y-K, Kim S-N. Humanistic approach to well-being. J Korea Entertainment Industry Association. 2019;13(7):321–46.
39. Chopra S, Kauts A. Development of collaborative skills scale: reliability and validity. MIER J Educ Stud Trends Pract. 2023: 81–97. ISSN 0976-8203. https://doi.org/10.52634/mier/2023/v13/i1/2376.
40. Chopra S, Kauts A. Development of collaborative skills scale: reliability and validity. MIER J Educ Stud Trends Pract. 2023;81–97.
41. Cohen J. Social, emotional, ethical, and academic education: creating a climate for learning, participation in democracy, and well-being. Harv Educ Rev. 2006;76(2):201–37.
42. Damayanti D, Farihah U, Mislikhah M. Implementation of humanistic learning theory in science and technology learning towards students' creative thinking skills. Edu Soc J. 2023;1(1):24–31.
43. Dang J, Liu L. Dehumanization risks associated with artificial intelligence use. American Psychologist, 2025.
44. Davis CM. What is empathy, and can empathy be taught? Phys Ther. 1990;70(11):707–11.
45. Deep PD, Ghosh N, Chen Y. Faculty burnout in higher education: effects on student engagement, learning outcomes, and artificial intelligence-driven institutional responses. J Edu Dev Psychol. 2025;15(1):29.
46. Dijkstra TK, Henseler J. Consistent and asymptotically normal pls estimators for linear structural equations. Comput Stat Data Anal. 2015;81:10–23.
47. Dost G. Student well-being: the impact of belonging, covid-19 pandemic related student stress, loneliness, and academic anxiety. Front Psychol. 2025;16:1481328.
48. Douwes R, Metselaar J, Pijnenborg GHM, Boonstra N. Well-being of students in higher education: the importance of a student perspective. Cogent Education. 2023;10(1):2190697.
49. Dubois D. Paradoxes of generative ai: both promise and threat to academic freedom. AAUP J Acad Freedom. 2024;15.
50. Elhadary Y, Abdelatti H. Gender equality at public universities in Saudi Arabia: achievements and ambitions. 2024.
51. Ercikan K. Limitations in sample-to-population generalizing. In: Generalizing from educational research. Routledge; 2009. p. 221–244.
52. Essel HB, Vlachopoulos D, Essuman AB, Amankwa JO. Chatgpt effects on cognitive skills of undergraduate students: receiving instant responses from ai-based conversational large language models (llms). Comput Edu Artifi Intell. 2024;6:100198.
53. Ferguson T, Roofe CG. Sdg 4 in higher education: challenges and opportunities. Int J Sustain High Educ. 2020;21(5):959–75.
54. Fornell C, Larcker DF. Evaluating structural equation models with unobservable variables and measurement error. J Mark Res. 1981;18(1):39–50.
55. Freeman J. Student generative ai survey 2025. Technical report, Higher Education Policy Institute (HEPI), 2025. URL https://www.hepi.ac.uk/2025/02/26/student-generative-ai-survey-2025/. Survey of 1,041 full-time undergraduate students on generative AI usage.
56. Gaete J, Montero-Marin J, Rojas-Barahona CA, Olivares E, Araya R. Validation of the spanish version of the psychological sense of school membership (pssm) scale in chilean adolescents and its association with school-related outcomes and substance use. Front Psychol. 2016;7:1901.
57. General Authority for Statistics. General authority for statistics official website. https://www.stats.gov.sa/en/, 2025. Accessed June 12, 2025, to ensure the most current information from the official statistical authority of Saudi Arabia.
58. Gervais SJ, Bernard P, Klein O, Allen J. Toward a unified theory of objectification and dehumanization. In Objectification and (de) humanization: 60th Nebraska symposium on motivation, pp. 1–23. Springer, 2013.
59. Ghimire A, Edwards J. Generative ai adoption in classroom in context of technology acceptance model (tam) and the innovation diffusion theory (idt). arXiv preprint arXiv:2406.15360, 2024.
60. Ghosh S. Rehumanizing education in the age of technology. In: Advances in technological innovations in higher education. CRC Press; 2024. p. 1–15.
61. Gomez-Lopez M, Viejo C, Romera EM, Ortega-Ruiz R. Psychological well-being and social competence during adolescence: longitudinal association between the two phenomena. Child Indic Res. 2022;15(3):1043–61.
62. Gopalan M, Brady ST. College students' sense of belonging: a national perspective. Educ Res. 2020;49(2):134–7.
63. Grassini S. Development and validation of the ai attitude scale (aias-4): a brief measure of general attitude toward artificial intelligence. Front Psychol. 2023;14:1191628.
64. Hagerty BMK, Patusky K. Developing a measure of sense of belonging. Nurs Res. 1995;44(1):9–13.
65. Hair JF. Multivariate data analysis: an overview. International encyclopedia of statistical science; 2011. p. 904–7.
66. Hair JF Jr, Hult GTM, Ringle CM, Sarstedt M. A primer on partial least squares structural equation modeling (PLS-SEM). SAGE Publications, Inc., Thousand Oaks, CA, 3rd edition, 2021. ISBN 9781544396408. URL https://uk.sagepub.com/en-gb/eur/a-primer-on-partial-least-squares-structural-equation-modeling-pls-sem/book270548.
67. Hamington M. Social readiness: care ethics and migration. Compassionate migration and regional policy in the Americas; 2017. p. 237–52.
68. Hannan E, Liu S. Ai: new source of competitiveness in higher education. Compet Rev Int Bus J. 2023;33(2):265–79.

69. Hashem R, Ali N, El Zein F, Fidalgo P, Khurma OA. Ai to the rescue: Exploring the potential of chatgpt as a teacher ally for workload relief and burnout prevention. Res. Pract Technol Enhanc Learn. 2024;19.
70. Haslam N. Dehumanization and the lack of social connection. Curr Opin Psychol. 2022;43:312–6.
71. Haslam N, Stratemeyer M. Recent research on dehumanization. Curr Opin Psychol. 2016;11:25–9.
72. Heale R, Forbes D. Understanding triangulation in research evidence-based nursing. 2013;16(4):98.
73. Henseler J. Bridging design and behavioral research with variance-based structural equation modeling. J Advert. 2017;46(1):178–92.
74. Hignett S, McDermott H. Qualitative methodology. Evaluation of human work; 2015. p. 119–38.
75. Hinyard L, Toomey E, Eliot K, Breitbach A. Student perceptions of collaboration skills in an interprofessional context: development and initial validation of the self-assessed collaboration skills instrument. Eval Health Prof. 2019;42(4):450–72.
76. Holmes W. Aied-coming of age? Int J Artif Intell Educ. 2024;34(1):1–11.
77. Holmes W, Tuomi I. State of the art and practice in ai in education. Eur J Educ. 2022;57(4):542–70.
78. Holmes W, Bialik M, Fadel C. Artificial intelligence in education promises and implications for teaching and learning. Center for Curriculum Redesign; 2019.
79. Hou I, Man O, Hamilton K, Muthusekaran S, Johnykutty J, Zadeh L, MacNeil S. all roads lead to chatgpt: How generative ai is eroding social interactions and student learning communities. arXiv preprint arXiv:2504.09779, 2025.
80. Huang T. Using sor framework to explore the driving factors of older adults smartphone use behavior. Humanit Soc Sci Commun. 2023;10(1):1–16.
81. Hurst B, Wallace RR, Nixon SB. The impact of social interaction on student learning. Reading horizons, 2013.
82. Hussein A. The use of triangulation in social sciences research: can qualitative and quantitative methods be combined? J Compar Soc work. 2009;4(1):106–17.
83. Ingle M. Dehumanization linked to poorer mental and physical health. https://www.madinamerica.com/2019/11/dehumanization-linked-poorer-mental-physical-health/, November 2019. Mad in America.
84. Ivanov S, Soliman M, Tuomi A, Alkathiri NA, Al-Alawi AN. Drivers of generative ai adoption in higher education through the lens of the theory of planned behaviour. Technol Soc. 2024;77:102521.
85. Jackson LA, Ervin KS, Gardner PD, Schmitt N. Gender and the internet: women communicating and men searching. Sex Roles. 2001;44:363–79.
86. Jenkins TA, Robison M, Joiner TE. Dehumanization and mental health: clinical implications and future directions. Curr Opin Behav Sci. 2023;50:101257.
87. Jobin A, Ienca M, Vayena E. The global landscape of ai ethics guidelines. Nature Mach Intell. 2019;1(9):389–99.
88. Johnson AP. Humanistic learning theory. Education psychology: theories of learning and human development; 2014. pp. 1–10.
89. Jukiewicz M. How generative artificial intelligence transforms teaching and influences student wellbeing in future education. Front Educ. 2025;10:1594572.
90. Kang H. The prevention and handling of the missing data. Korean J Anesthesiol. 2013;64(5):402–6.
91. Khalili K. The effects of ai overreliance on student higher-order thinking skills development. Speech Language. 2025;11(2):989–1002.
92. Khoza NG, Van Der Walt F. A systematic review on ai-enhanced pedagogies in higher education in the global south. Front Educ. 2025;10:1667884.
93. Kim H-Y, McGill AL. Ai-induced dehumanization. J Consum Psychol. 2024.
94. Kleinsmann M, Deken F, Dong A, Lauche K. Development of design collaboration skills. J Eng Des. 2012;23(7):485–506.
95. Klimova B, Pikhart M. Exploring the effects of artificial intelligence on student and academic well-being in higher education: A mini-review. Front Psychol. 2025;16:1498132.
96. Kline RB. Principles and practice of structural equation modeling. Guilford Publications; 2023.
97. Korkmaz Ö, Çakir R, Yaşar M, Özden. A validity and reliability study of the computational thinking scales (cts). Comput Hum Behav. 2017;72:558–69.
98. Krassadaki E, Matsatsinis N. Career options and necessary technical skills in ai. In: Handbook of research on artificial intelligence, innovation and entrepreneurship. Edward Elgar Publishing; 2023. p. 350–366.
99. Kumar S. Developing human skills in the era of artificial intelligence: Challenges and opportunities for education and training. Scholedge International Journal of Multidisciplinary & Allied Studies. 2023;10(2).
100. Laajaj R, Macours K. Measuring skills in developing countries. J Human Res. 2019;56(4):1–46. https://doi.org/10.3368/jhr.56.4.1018-9805R1.
101. Lagerspetz O. Studying perception. Philosophy. 2008;83(2):193–211.
102. Lai PC. The literature review of technology adoption models and theories for the novelty technology. J Info Sys Tech Manage 2017;14(1):21–38. ISSN 18071775. https://doi.org/10.4301/S1807-17752017000100002. URL https://www.tecsi.org/jistem/index.php/jistem/article/view/10.4301%25S1807-17752017000100002/643.
103. Lai T, Xie C, Ruan M, Wang Z, Hong L, Shimin F. Influence of artificial intelligence in education on adolescents' social adaptability: the mediatory role of social support. PLoS ONE. 2023;18(3):e0283170.
104. Lawrie SI, Carter DB, Nylund-Gibson K, Kim HS. A tale of two belongings: social and academic belonging differentially shape academic and psychological outcomes among university students. Front Psychol. 2025;15:1394588.
105. Lee W, Yang H. A study on the intention to use personal mobility services: focused on the sor (stimulus-organism-response) model. Info Sys Rev. 2022;24(2):67–88.
106. Leguina A. A primer on partial least squares structural equation modeling (pls-sem), 2015.
107. Li P, Liu Y, Yang J, Ren S. Towards socially and environmentally responsible ai. arXiv preprint arXiv:2407.05176, 2024.
108. Llorent VJ, González-Gómez AL, Farrington DP, Zych I. Social and emotional competencies and empathy as predictors of literacy competence. Psicothema. 2020;32(1):47–53. https://doi.org/10.7334/psicothema2019.106.
109. Loeb S, Dynarski S, McFarland D, Morris P, Reardon S, Reber S. Descriptive analysis in education: a guide for researchers. ncee 2017-4023. National Center for Education Evaluation and Regional Assistance; 2017.
110. Ma D, Akram H, I-Hua Chen. Artificial intelligence in higher education: a cross-cultural examination of students' behavioral intentions and attitudes. Int Rev Res Open Distrib Learn. 2024;25(3):134–57.

111. Macnamara BN, Ibrahim Berber M, Çavuşoğlu C, Krupinski EA, Nallapareddy N, Nelson NE, et al. Does using artificial intelligence assistance accelerate skill decay and hinder skill development without performers' awareness? Cogn Res Principles Implications. 2024;9(1):46.
112. Madaio M, Kapania S, Qadri R, Wang D, Zaldivar A, Denton R, Wilcox L. Learning about responsible ai on-the-job: Learning pathways, orientations, and aspirations. In: Proceedings of the 2024 ACM conference on fairness, accountability, and transparency; 2024. p. 1544–58.
113. Makaremi N, Yildirim S, Morgan GT, Touchie MF, Alstan Jakubiec J, Robinson JB. Impact of classroom environment on student wellbeing in higher education: review and future directions. Build Environ. 2024;265:111958.
114. Makweya PP, Sepadi M. The crucial role of empathy in fostering inclusive learning environments. In: Global practices in inclusive education curriculum and policy. IGI Global; 2025. p. 77–90.
115. Malakcioglu C. Empathy assessment scale. Northern Clin Istanbul. 2022;9(4):358.
116. Malone GP, Pillow DR, Osman A. The general belongingness scale (gbs): Assessing achieved belongingness. Personality Individ Differ. 2012;52(3):311–6.
117. Marrone R, Taddeo V, Hill G. Creativity and artificial intelligence-a student perspective. J Intelligence. 2022;10(3):65.
118. Mason Stephens J, Iasiello M, Ali K, van Agteren J, Fassnacht DB. The importance of measuring mental wellbeing in the context of psychological distress: using a theoretical framework to test the dual-continua model of mental health. Behav Sci. 2023;13(5):436.
119. McHugh JE, Power CH, Carney S, Lawlor BA. Exploring the meaning of loneliness among socially isolated older adults in rural ireland: a qualitative investigation. Qual Res Psychol. 2017;14(4):394–414.
120. Mey G. Qualitative methodology. In: International handbook of psychology learning and teaching. Springer; 2022. p. 1–26.
121. Morandini S, Fraboni F, De Angelis M, Puzzo G, Giusino D, Pietrantoni L, et al. The impact of artificial intelligence on workers' skills: upskilling and reskilling in organisations. Informing Sci. 2023;26:39–68.
122. Mossman SA, Luft MJ, Schroeder HK, Varney ST, Fleck DE, Barzman DH, et al. The generalized anxiety disorder 7-item scale in adolescents with generalized anxiety disorder: signal detection and validation. Ann Clin Psychiatry. 2017;29(4):227–34.
123. Msambwa MM, Wen Z, Daniel K. The impact of ai on the personal and collaborative learning environments in higher education. Eur J Educ. 2025;60(1):e12909.
124. Musavian SS, Talaee E, Fardanesh H. Investigating students empathy and their school learning behaviors using artificial intelligence methods. Edu Strateg Med Sci. 2019;12(3):23–30.
125. Bin Nasir AN, Ali DF, Bin Noordin MK, Malaysia Skudai UT. Technical skills and non-technical skills: predefinition concept Mohd Safarin Bin NORDIN. Technical report, 2011.
126. Nardi PM. Doing survey research: a guide to quantitative methods. Routledge; 2018.
127. Newman DA. Missing data: five practical guidelines. Organ Res Methods. 2014;17(4):372–411.
128. Nneji BU. Technologies in education and the dehumanization and imperialization of pedagogy: the African perspective. Bulg J Sci Educ Policy. 2014;8(1):86.
129. Norberg K, Murphy A, De Ley L, Moltz ES, Almoubayyed H, Ritter S. Using generative ai to foster student sense of belonging in mathematics. In: International conference on artificial intelligence in education. Springer; 2025. p. 188–95.
130. Obst P, Shakespeare-Finch J, Krosch DJ, Rogers EJ. Reliability and validity of the brief 2-way social support scale: an investigation of social support in promoting older adult well-being. SAGE Open Med. 2019;7:2050312119836020.
131. Oei TPS, Sawang S, Goh YW, Mukhtar F. Using the depression anxiety stress scale 21 (dass-21) across cultures. Int J Psychol. 2013;48(6):1018–29.
132. Okay-Somerville B, Scholarios D. A multilevel examination of skills-oriented human resource management and perceived skill utilization during recession: Implications for the well-being of all workers. Hum Resour Manage. 2019;58(2):139–54.
133. Over H, Cook R. Perceptual dehumanization theory: a critique. Psychol Rev. 2023;130(5):1401.
134. Oviatt S. Technology as infrastructure for dehumanization: three hundred million people with the same face. In: Proceedings of the 2021 international conference on multimodal interaction; 2021. p. 278–87.
135. Pallant JL, Blijlevens J, Campbell A, Jopp R. Mastering knowledge: the impact of generative ai on student learning outcomes. Studies in Higher Education; 2025. p. 1–22.
136. Panayiotou M, Badcock JC, Lim MH, Banissy MJ, Qualter P. Measuring loneliness in different age groups: the measurement invariance of the ucla loneliness scale. Assessment. 2023;30(5):1688–715.
137. Pandit S, Sarkar SK, Barik S, Sahu S. Ai in skill development, critical thinking, digital literacy, and ai-driven job preparation. In: Impacts of AI on students and teachers in education 5.0. IGI Global Scientific Publishing; 2025. p. 23–76.
138. Pani B, Crawford J, Allen K-A. Can generative artificial intelligence foster belongingness, social support, and reduce loneliness? A conceptual analysis. Applications of generative AI; 2024. p. 261–76.
139. Păvăloaia V-D, Necula S-C. Artificial intelligence as a disruptive technology-a systematic literature review. Electronics. 2023;12(5):1102.
140. Peng C, Kim YG. Application of the stimuli-organism-response (sor) framework to online shopping behavior. J Int Commerce. 2014;13(3–4):159–76.
141. Perry A, Karpova E. Efficacy of teaching creative thinking skills: a comparison of multiple creativity assessments. Think Ski Creat. 2017;24:118–26. https://doi.org/10.1016/j.tsc.2017.02.017.
142. Perry A, Karpova E. Efficacy of teaching creative thinking skills: a comparison of multiple creativity assessments. Think Ski Creat. 2017;24:118–26.
143. Pervaiz H, Ali K, Razzaq S, Tariq M. The impact of ai on critical thinking and writing skills in higher education. Critic Rev Soc Sci Stud. 2025;3(1):3165–76.
144. Pinaki Mondal PM, Basu M, Bhadoria PBS. Critical review of precision agriculture technologies and its scope of adoption in India; 2011.
145. Qasmi F, Fatima SK. Enhancing education and well-being through artificial intelligence: opportunities and challenges. In: International conference on breaking barriers with generative intelligence. Springer; 2024. pp. 154–64.
146. Radloff LS. The ces-d scale: a self-report depression scale for research in the general population. Appl Psychol Meas. 1977;1(3):385–401.
147. Ratka A. Empathy and the development of affective skills. Am J Pharm Educ. 2018;82(10):7192.
148. Renz A, Krishnaraja S. Toward responsible, human-centered ai in edtech. In: ISPIM conference proceedings. The International Society for Professional Innovation Management (ISPIM); 2020. p. 1–10.

149. Rogers EM, Singhal A, Quinlan MM. Diffusion of innovations. In: An integrated approach to communication theory and research. Routledge; 2014. p. 432–48.
150. Rosa MC. Theories of the south: limits and perspectives of an emergent movement in social sciences. Curr Sociol. 2014;62(6):851–67.
151. Rusandi MA, Ahman IS, Khairun DY, Mutmainnah. No worries with chatgpt: building bridges between artificial intelligence and education with critical thinking soft skills. J Public Health. 2023;45(3):e602–3.
152. Russell G, Topham P. The impact of social anxiety on student learning and well-being in higher education. J Ment Health. 2012;21(4):375–85.
153. Sack N. Creative skills in crisis: A constructivist critique of ai replacing creative skills. Master's thesis, Utrecht University, 2025. https://studenttheses.uu.nl/handle/20.500.12932/49227.
154. Said SA, Abdallah W. with sustainable development goal 4. Bus Dev AI Digitalization. 2024;2(2):259.
155. Sargiotis D. Fostering ethical and inclusive ai: a human-centric paradigm for social impact. Available at SSRN 4879372, 2024.
156. Sarstedt M, Ringle CM, Hair JF. Partial least squares structural equation modeling. In Handbook of market research. Springer; 2021. p. 587–632.
157. Sartori L, Theodorou A. A sociotechnical perspective for the future of ai: narratives, inequalities, and human control. Ethics Inf Technol. 2022;24(1):4.
158. Săseanu AS, Gogonea R-M, Ghiță SI. The social impact of using artificial intelligence in education. Amfiteatru Econ. 2024;26(65):89–105.
159. Schultz MD, Clegg M, Hofstetter R, Seele P. Algorithms and dehumanization: a definition and avoidance model. AI Soc. 2025;40(4):2191–211.
160. Sethi SS, Jain K. Ai technologies for social emotional learning: recent research and future directions. J Res Inno Teach Learn. 2024;17(2):213–25.
161. Sharma R, Mishra R. A review of evolution of theories and models of technology adoption. Indore Manage J. 2014;6(2):17–29.
162. Shaw ML, Plapinger E. Ethical guidelines. Disp Resol Mag. 2000;7:14.
163. Shawe-Taylor J, Dignum F. Human-centric ai and education. J Artifi Intell Sustainable Dev. 2024;1(1):1–4.
164. Shin HI, Kim J. My computer is more thoughtful than you: loneliness, anthropomorphism and dehumanization. Curr Psychol. 2020;39(2):445–53.
165. Shiohira K. Understanding the impact of artificial intelligence on skills development. education 2030. UNESCO-UNEVOC International Centre for Technical and Vocational Education and Training; 2021.
166. Shyroka S, Bilchuk N, Piven H. Dehumanization in the digital educational process: philosophical analysis of problems and risks of the modern education system. 2023.
167. Simmering VR, Lu O, Bolsinova M. What technology can and cannot do to support assessment of non-cognitive skills. Front Psychol. 2019;10:2168.
168. Sin KY, Osman A, Salahuddin SN, Abdullah S, Lim YJ, Sim CL. Relative advantage and competitive pressure towards implementation of e-commerce: overview of small and medium enterprises (smes). Procedia Econ Financ. 2016;35:434–43.
169. Slovák P, Wadley G, Coyle D, Thieme A, Yamashita N, Lederman R, Schutt S, Doces M. Developing skills for social and emotional wellbeing. In: Proceedings of the 33rd annual ACM conference extended abstracts on human factors in computing systems; 2015. p. 2397–400.
170. Smith WG. Does gender influence online survey participation? A record-linkage analysis of university faculty online survey response behavior. Online submission, 2008.
171. Solaiman I, Talat Z, Agnew W, Ahmad L, Baker D, Blodgett SL, Chen C, Daumé III H, Dodge J, Duan I, et al. Evaluating the social impact of generative ai systems in systems and society. arXiv preprint arXiv:2306.05949, 2023.
172. Sosu EM. The development and psychometric validation of a critical thinking disposition scale. Think Ski Creat. 2013;9:107–19.
173. Sovey S, Osman K, Mohd-Matore ME, et al. Exploratory and confirmatory factor analysis for disposition levels of computational thinking instrument among secondary school students. Euro J Edu Res. 2022;11(2):639–52.
174. Spatola N, Kühnlenz B, Cheng G. Perception and evaluation in human-robot interaction: the human-robot interaction evaluation scale (hries)-a multicomponent approach of anthropomorphism. Int J Soc Robot. 2021;13(7):1517–39.
175. Stewart L. Operationalization | definition, steps & guide. https://atlasti.com/research-hub/operationalization, 2024. Accessed 08 Jul 2025.
176. Sultanova G, Shilibekova A, Rakhymbayeva Z, Rakhimbekova A, Shora N. Exploring the influence of non-cognitive skills on academic achievement in stem education: the case of kazakhstan. Front Educ. 2024;9:1339625.
177. Supovitz JA, Klein V. Mapping a course for improved student learning: How innovative schools systematically use student performance data to guide improvement. Consortium for Policy Research in Education Philadelphia, PA, 2003.
178. Surve BC, Londhe BR. Artificial intelligence based assessment and development of student's non-cognitive skills in professional education through an online learning management system. In: 2020 fourth international conference on inventive systems and control (ICISC). IEEE; 2020. p. 329–36.
179. Susskind R, Susskind D. The future of the professions: how technology will transform the work of human experts. Oxford: Oxford University Press; 2022.
180. Szmyd K, Mitera E. The impact of artificial intelligence on the development of critical thinking skills in students. Euro Res Stud J. 2024;27(2):1022–39.
181. Ting H, Memon MA, Thurasamy R, Cheah J-H. Snowball sampling: a review and guidelines for survey research. Asian J Bus Res (AJBR). 2025;15(1).
182. Torres A, Wenke M, Lieneck C, Ramamonjiarivelo Z, Ari A. A systematic review of artificial intelligence used to predict loneliness, social isolation, and drug use during the covid-19 pandemic. J Multidisc Healthcare. 2024:3403–25.
183. Tuomi I. Artificial intelligence, 21st century competences, and socio-emotional learning in education: more than high-risk? Eur J Educ. 2022;57(4):601–19.
184. Turkkan Zencirli B, Altin M. The impact of artificial intelligence on workplace dehumanization: a critical review. J Hospital Tourism Horizons. 2025;1(2):128–49.
185. Vallor S. The AI mirror: how to reclaim our humanity in an age of machine thinking. Oxford: Oxford University Press; 2024.

186. Van NT, Mohd Daril MA, Ali M, Korejo MS. Enhancing psychological well-being in higher education post-covid-19 pandemic. the role of ai-based support systems-bibliometric reviews. Int J Online Biomed Eng. 2024;20(6).
187. Wang B, Rau P-LP, Yuan T. Measuring user competence in using artificial intelligence: validity and reliability of artificial intelligence literacy scale. Behav Inform Technol. 2023;42(9):1324–37.
188. Wang H, Zou J, Mozer M, Goyal A, Lamb A, Zhang L, Su WJ, Deng Z, Xie MQ, Brown H, et al. Can ai be as creative as humans? arXiv preprint arXiv:2401.01623, 2024.
189. Wang Y-M, Wei C-L, Lin H-H, Wang S-C, Wang Y-S. What drives students' ai learning behavior: a perspective of ai anxiety. Interact Learn Environ. 2022:1–17.
190. Wells CS. Assessing measurement invariance for applied research. Cambridge University Press; 2021.
191. White MA. New international research priorities for wellbeing education. In: New research and possibilities in wellbeing education. Springer; 2023. p. 385–402.
192. Williamson B, Eynon R. Historical threads, missing links, and future directions in ai in education, 2020.
193. Wrahatnolo T, Munoto. 21st centuries skill implication on educational system. In IOP Conference Series: Materials Science and Engineering, volume 296. Institute of Physics Publishing, 2 2018. https://doi.org/10.1088/1757-899X/296/1/012036.
194. Wunsch G. Introduction to demographic analysis: principles and methods. Berlin: Springer Science & Business Media; 2012.
195. Xusheng Q, Komolafe BF. Critical thinking an antidote to artificial intelligence threat: an innovation in teacher education practices: an innovation in teacher education practices. In Proce Int Conf Edu. 2020;6:51–6.
196. Yadav K. Disruptive innovative technologies in higher education. Int J Adv Edu Res. 2019;4(1):49–54.
197. Yano K. The science of human interaction and teaching. Mind Brain Educ. 2013;7(1):19–29.
198. Zhai C, Wibowo S, Li LD. The effects of over-reliance on ai dialogue systems on students' cognitive abilities: a systematic review. mart Learn Environ. 2024;11(1):28.
199. Zhao Y, Yin D, Wang L, Yihua Yu. The rise of artificial intelligence, the fall of human wellbeing? Int J Soc Welf. 2024;33(1):75–105.
200. Zhou M, Ee J. Development and validation of the social emotional competence questionnaire (secq). 2012.
201. Zoto E, Kianpour M, Kowalski S, Lopez-Rojas E. A socio-technical systems approach to design and support systems thinking in cybersecurity and risk management education. Complex Syst Inform Model Q. 2019;18:65–75.
202. Zung WWK. A self-rating depression scale. Arch Gen Psychiatry. 1965;12(1):63–70.
203. Zych I, Ortega-Ruiz R, Muñoz-Morales R, Llorent VJ. Dimensions and psychometric properties of the social and emotional competencies questionnaire (sec-q) in youth and adolescents. Revista latinoamericana de psicología. 2018;50(2):98–106.