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Integrating Artificial Intelligence (AI) Into Adult Education:
Opportunities, Challenges, and Future Directions

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ABSTRACT

This conceptual article provides a comprehensive overview of the current status of Artificial Intelligence (AI) integration and its influence on adult education. It discusses generative AI technologies and their potential applications in adult education settings, examines the opportunities and ethical challenges associated with integrating AI, and provides insights into emerging trends. The article consists of five sections. The introduction provides a rationale as to why AI should be integrated into adult education. Second, it describes evolving AI technologies such as Large Language Models (LLM) for personalized learning, Machine Learning Algorithms for adaptive learning systems, Virtual Reality (VR) and Augmented Reality (AR) for immersive learning experiences, Chatbots and virtual assistants for learner support and guidance, and Data Learning Analytics (DLA) for tracking learner progress and performance into adult education. Section three explores the ethical implications of AI in adult education, including academic honesty and integrity, data privacy, and algorithmic bias. In section four, emerging trends and future directions are discussed. The final section considers policy implications and makes recommendations for adult educators working to develop AI-enriched adult education.

KEYWORDS

Adaptive Learning Systems, Adult Education, Artificial Intelligence (AI), Augmented Reality, Content Generation, Machine Learning Systems, Natural Language Processing (NLP)

The International Standard Classification of Education defines adult learning as specifically targeting individuals who are regarded as adults by the society to which they belong to improve their technical or professional qualifications, further develop their abilities, enrich their knowledge to complete a level of formal education, or acquire knowledge, skills, and competencies in a new field or to refresh or update their knowledge in a particular field. This also includes what may be referred to as 'continuing education,' 'recurrent education,' or 'second chance education. (United Nations Educational, Scientific and Cultural Organization, Institute for Statistics, 2012, p. 78)

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A broad definition of AI: "Computers which perform cognitive tasks, usually associated with human minds, particularly learning and problem-solving" (p. 10). AI is not a single technology but an umbrella term that describes a range of technologies and methods, such as machine learning, natural language processing, data mining, neural networks, or algorithms. (Baker & Smith, 2019)

1. INTRODUCTION

According to the Organization for Economic Cooperation and Development (Verhagen, 2021), AI can improve and replace current technologies in delivering training, spreading information on skill requirements and relevant training courses, and personalizing the matching of job seekers to available learning opportunities. Adult learners, as digital natives, are comfortable using generative AI tools to access information and with education institutions diving deep into the analyses of large databases to track their progress and performance (Impact Research, 2023).

To prepare the global workforce to transition from an information society to an intelligent society, the United Nations Educational, Scientific and Cultural Organization (UNESCO) developed a global framework to help define and measure digital literacy (2018). The framework has seven competency areas: devices and software operations, information and data literacy, communication and cooperation, digital content creation, safety, problem-solving, and career-related competencies, which suggest that AI's application in adult education is strategically significant to training an innovative, scientific, and technologically talented workforce. Such a move requires educators to develop an open, flexible, active, and innovative adult education ecosystem to promote quality education and ensure education equity (Kang, 2023). In 2019, UNESCO published a report entitled "Artificial Intelligence in Education: Challenges and Opportunities for Sustainable Development," which highlighted the increasing role of AI in influencing students' access to education, learning performance, teaching andragogy, educational data analysis and management.

The World Economic Forum (WEF) estimates that almost one-third of all jobs worldwide are likely to be transformed by technology in the next decade (Zahidi, 2020) and that essential technical and vocational skills are currently underemphasized in education systems (Strategic Intelligence, 2020). Consequently, there is an urgent need to replace the traditional andragogical model of adult training with a new dynamic structural model (Storey & Beeman, 2023), more suited to creating new learning content. Generative AI tools are ideally positioned to fill this role, given their ability to access and synthesize a wide range of human knowledge into specific outputs (Leiker et al., 2023). However, it is challenging to create this new path as it depends on adult educators having the required knowledge and skills. It is, therefore, incumbent on all educators to continue their learning to adapt, overcome barriers, and effectively integrate AI into programs for future developments (Kaliisa et al., 2022).

The subsequent sections of this article are organized into four distinct parts. Section 2 presents an overview of AI-driven educational technologies within the context of adult learning and discusses the challenges of integrating AI into adult education. Section 3 explores the ethical implications of AI in adult education, including academic integrity, data privacy, algorithmic bias, and copyright. Section 4 is focused on emerging trends and future directions for adult education. Finally, policy implications and recommendations for adult educators are made to develop AI-enriched adult education.

2. INTEGRATING AI INTO ADULT EDUCATION

This section discusses the evolution of computer-assisted learning in adult education and the emerging role and capabilities of generative AI machine learning technologies such as Large Language Models (LLM), Machine Learning Algorithms for Adaptive Learning Systems (ALS), Virtual Reality (VR), and Augmented Reality (AR) for immersive learning experiences, Chatbots and virtual assistants for learner support and guidance, and Data Analytics (DA) for tracking learner progress and performance in the adult education environment. Table 1 summarizes each AI technology; a deeper discussion follows in Section 2.1.

Table 1. Definitions for and Examples of Generative AI Machine Learning Technologies

Generative AI Technologies	Brief Definition	Examples/Applications
Large Language Models (LLM)	AI trained to recognize and generate text and other tasks (Milana et al., 2024).	ChatGPT (OpenAI) Gemini (Google) Chatbots
Adaptive Learning Systems (ALS)	Data-driven system that adapts to and customizes instruction for individual learners (Pugliese, 2017).	Intelligent Tutoring Systems Duolingo Aleks
Learning Analytics (LA)	Using data about learners to optimize learning and the learning environment (Siemens & Baker, 2012).	Degree Compass eAdvisor
Virtual Reality (VR) and Augmented Reality (AR)	Immersive learning experiences to promote skills development and deep learning of complex concepts (Blaha, 2016; Koumpouros, 2024).	Oculus Rift TeachLivE™

Integrating these generative AI technologies into adult learning curricula can challenge traditional adult education practices (Kang, 2023) as it requires transitioning from teaching-oriented to learning-oriented control. However, it is argued that this transition is imperative for educators to use readily available AI-assisted tools that provide learners with differentiated instruction, a personalized learning plan consisting of suitable content, learning activities that match their learning characteristics, and assessments that evaluate their academic performance. With this assistance, adult learning quality will improve and be more effective (Kang, 2023).

2.1 Evolution of Computer-Assisted Learning in Adult Education

Computer-Assisted-Instruction (CAI) courseware used to teach remote adult learners is an early example of AI application in adult education. Teachers' instructions and learning materials were recorded on CDs (audio) or DVDs (video) and sent to adult learners. Adult learners could access quality education by interacting with teacher presentations at their own pace (Kang, 2023). In the later development of internet technology, students could learn remotely and participate in classes online. Computers began to support teachers by automatically grading exams (limited to objective questions such as multiple choice, right or wrong questions, etc.). Today, virtual teaching assistants can take over tasks such as assigning individual and group learning activities, distributing and collecting homework, answering repetitive questions, and grading assignments with customized feedback (Kang, 2023).

The first chatbot, ELIZA, was created by Joseph Weizenbaum in the mid-1960s, leveraging a basic type of natural language processing (NLP). ELIZA was originally run on a mainframe at the Massachusetts Institute of Technology before being implemented on numerous more modern computers. ELIZA's text-based interface also influenced a whole genre of video games. Warner Books published the first well-known work of fiction written by an AI in 1984 (Ciesla, 2024).

2.2 Emerging Roles and Capabilities of AI

2.2.1 Generative AI: Machine Learning Technology

Large Language Models (LLMs). Large language models (LLMs) are AI-trained to generate text similar to human-generated text (Floridi, 2023; Milana et al., 2024; Tate et al., 2023). The introduction of ChatGPT in November 2022 was a game changer not just in the educational context but in all aspects of living due to its accessibility via a conversational interface, which allows users to communicate with the AI in a human-like way (Kasneci et al., 2023). LLMs like ChatGPT, BERT, Ro-BERTa, and XLNet, all created by prominent tech companies (OpenAI, Google, and Microsoft), are impressive in various language-related tasks (Adiguzel et al., 2023; Kasneci et al., 2023; Tate et al., 2023).

Practical Applications and Implications. LLMs attract adult learners because they offer instant feedback to refine their writing, including word choice and grammar, generate ideas, and explore various topics (Anders, 2023). LLMs can also be employed as a starting point for idea generation, sparking creativity and facilitating the writing process (Adiguzel et al., 2023; Labadze et al., 2023; McKnight, 2021; Tlili et al., 2023).

Chatbots can help support teaching (Gimpel et al., 2023) and assist with routine tasks like scheduling, grading, and providing differentiated materials (Labadze et al., 2023). Gimpel et al. (2023) argue that teachers/instructors may use Chatbots to develop lecture ideas, draft plans and module descriptions, and craft announcement texts. In addition, Mollick and Mollick (2022) suggest using Chatbots to support learners with knowledge transfer by applying acquired knowledge to different situations, raising awareness of the limitations of their knowledge, and encouraging critical thinking about the information.

ChatGPT, for example, requires adequate prompts from the user to generate valuable results. Gimpel et al. (2023) argue that crafting such prompts, as much as evaluating the quality of the results, requires users to logically organize and categorize information coherently, which can help structure the learners' thinking, and that multiple Chatbot interactions on the same topic can help refine the text-generation process. Rice et al. (2024) advise that ChatGPT could help students in the research process by identifying relevant literature, evaluating sources, extracting, synthesizing, and summarizing information from those sources, helping identify research gaps, generating hypotheses, and aiding researchers in developing well-defined questions to guide further research. Moreover, ChatGPT can provide data collection techniques and sampling strategies by considering research objectives, constraints, and ethical considerations. Najafali et al. (2023) suggest that ChatGPT can aid in crafting the abstract and different parts of a research grant (e.g., aims, hypothesis, and significance of the proposed project).

Jill Watson is an example of an early Chatbot as both a teacher/instructor and student assistant. Developed by the Georgia Institute of Technology (Goel, 2016), Jill's job was to respond to students' basic online questions without the students realizing that it was software. This app later acquired additional functionalities, such as linking students with their peers, to increase motivation and support networks to help reduce the high dropout rates in online courses (Georgia Tech, 2020). Today, Chatbots are among the most widely used AI-based applications to answer general students' academic or social queries. Institutional admissions-related queries, guidance through admission procedures, and selecting and registering for the courses that best suit their educational and career goals can all be managed by a Chatbot.

The findings from a study by Leiker et al. (2023) that compared newly created course content using LLMs with traditional, human-created content found the two courses almost identical. The researchers concluded that LLMs can be a viable tool for making accurate and explicit educational content. Grounded on the outcome of this study, the researchers argue that AI, specifically LLMs, will reshape the adult learning, training, and upskilling landscape.

While LLMs, like ChatGPT, open new learning possibilities, they present new demands and challenges relating to assessment (Impact Research, 2023). For example, two months after ChatGPT's introduction (January 2023), Stanford University's school paper, The Stanford Daily, conducted an "informal poll" that showed 17% of 4497 respondents had used ChatGPT on their final exams. Most (59.2%) indicated they used the chatbot for brainstorming, outlining, and forming ideas, according to the poll; another 29.1% used it to answer multiple choice questions; and while 7.3% submitted written material from ChatGPT with edits, 5.5% said they submitted written material from ChatGPT unedited (Cu & Hochman, 2023). Educators, specifically adult educators, have an ethical responsibility to develop a student's moral compass for using generative AI tools. Chatbots are part of life and will be used irrespective of institutional guidance, but what is required is that due recognition is given to

Table 2. Descriptions of the Four Categories of Adaptive Learning Systems

Categories of ALS*	Description
Decision Tree	Utilizes a set of rules from pre-prescribed content modules organized in pre-prescribed sets of assessments and answer banks. Using intervals of data and feedback, learner workflows are created, and individualized work streams are assigned throughout a set pace.
Rules-Based	Work on a preconceived set of rules and are not designed around an algorithmic approach; a particular learning path is predetermined by rule sets that can change for individual learners. Students may take a differentiated path through assessment of prior knowledge and determine their own progression pace; ongoing feedback is provided, and remediation is prescribed based on the predetermined rules.
Machine Learning-Based	Utilizes pattern recognition, statistical modeling, and predictive analytics; uses programmed algorithms to make real-time predictions about a learner's mastery. System continually harvests data in real-time, determining students' proficiency in mastering learning objective-specific content; analyzes data in real-time, makes inferences, and uses it to automatically adjust the overall sequence of skills or the type of content that a student experiences.
Advanced Algorithm	Provide 1:1 computer-to-student interaction, making it scalable depending on the type of content (usually mathematics and sciences). Content modules are prescribed to students based on prior proven mastery of knowledge and applied knowledge activity; modules are tied to a specific, individual learner profile; learning paths, feedback, and content are evaluated in real-time by constantly analyzing data from the individual student and comparing it to other students exposed to the same or similar content.

*From "The Visualization for an Ideal Adaptable Learning Ecosystem" by L. Pugliese, 1EdTech Consortium Adaptive Learning Innovation Leadership Network [Paper Presentation], https://www.imsglobal.org/adaptive-adaptable-next-generation-personalized-learning

the writing partner and that without appropriate references, there will be consequences for plagiarism (Tlili et al., 2023).

2.2.2 Adaptative Learning Systems (ALS)

Adaptive learning is a technology and data-driven system of integrating instructional resources, learning objectives, and assessment activities into single, progressive modular learning elements that can be adapted to individual learners, reordered, or shared between learning systems (Pugliese, 2017). Adaptive eLearning Systems (AeLS) provide informative feedback to students and instructors and develop predictive models for anticipating academic success, identifying at-risk students, and providing actionable recommendations for targeted interventions (Siemens & Baker, 2012). Pugliese (2017) states that AeLS can be categorized into four cumulative adaptive categorical frameworks: decision tree (DT), rules-based (RB), machine learning-based (ML), and advanced algorithm (AA) adaptive systems. The description for each category is found in Table 2; they are listed in increasing complexity.

In an AeLS, with adaptivity, the learner's needs and preferences are adjusted by the system itself, and therefore, the system alters its behaviors appropriately. Adaptivity includes several AI methods, such as intelligent tutoring, knowledge representation, and learner modeling (Tseng et al., 2008). Salas-Pilco et al. (2022) argue that using ALS can enhance educational inclusivity by accommodating diverse adult learners through content adaptation and alternate formats.

Intelligent Tutoring Systems (ITS). Cognitive tutors are examples of ITS grounded in cognitive psychology (Mitrovic et al., 2003). Through sophisticated AI techniques, ITSs are adaptive instructional systems that provide automatic and cost-effective one-on-one instruction (Ong & Ramachandran, 2003). ITS seeks to simulate the "instructor" in real-life learning situations by monitoring and directing the student's lesson plans while adapting pedagogical strategies appropriate to students' understanding of the content (Rane et al., 2008). ITSs implement the Micro-adaptive approach by making inferences about students' characteristics to dynamically modify various aspects of the learning environment (Vandewaetere et al., 2011).

Practical Applications and Implications. A typical example of personalized learning is the Duolingo App, a language learning app with more than 300 million users worldwide. It learns where users are succeeding and failing to give them specific exercises to learn a new language (Peanandam, 2018). Another example of personalized learning is Gooru Navigator. This AI platform classifies learners' current knowledge, skills, and mindsets and matches learning objectives with learning content created by an open community of teachers (Tuomi, 2020). Aleks is also an AI system that uses personalized learning for math, chemistry, statistics, and accounting teaching; it is used by over 25 million students worldwide and identifies a student's current knowledge and what the student is ready to learn next (McGraw Hill, n.d.).

A 2023 winner of 1EdTech's Learning Impact Award was The University of Central Florida's (UCF) Personalized Adaptive Learning initiative, which provides adaptive learning, online homework, and assessment capabilities. In 2014, UCF began strategically implementing adaptive courseware to positively impact student success in gateway courses. In collaboration with 73 instructors and 43,898 students in 363 separate course sections, UCF's adaptive platform Realizeit delivered personalized adaptive learning (PAL) to students in subjects such as College Biology, Intermediate Algebra, College Algebra, College Physics I & II, Statistics for Educational Data, Elementary & Intermediate Spanish, Lodging Foundations, and Business which lead to increased rates of student success in key general education offerings and major-specific foundation courses (UCF, 2023). 1EdTech (2023) states that Learning Impact Award-winning projects provide evidence of significant benefits for student learning and institutional success.

Lim et al. (2023) conducted a study investigating the effects of AI-driven adaptive learning on adult learners in a workplace environment. The study's findings revealed that the implementation of ALS enhanced learning efficiency and positively impacted learners' self-confidence and motivation (Akbar et al., 2024). The findings of this study are consistent with the notion that tailored learning experiences can empower adult learners by fostering a sense of control over their educational journey.

2.2.3 Learning Analytics (LA)

According to the Society for Learning Analytics Research, LA is "the measurement, collection, analysis, and reporting of data about learners and their contexts for purposes of understanding and optimizing learning and the environment in which it occurs" (Siemens & Baker, 2012, pp.1-2). LA combines human judgment with evidence-based technology-enhanced learning (Brown, 2011) grounded on data analytics. The value of analytics in education relates to predicting student success, identifying at-risk students, and advising teachers about when and how to intervene.

Academic Analytics (AA). Academic Analytics (AA) explores organizational efficiencies by applying business intelligence methodologies and strategies in educational institutions (Howlin & Lynch 2014). Rich data help to guide decision-making for efficient practices across a wide range of logistical and academic issues, such as teaching spaces, faculty effectiveness, and students' retention of knowledge and skills (Freitas et al. 2015). The ultimate goal of AA is to refine the overall organizational delivery of learning rather than the delivery of instruction for individual learners or instructors at the course level (Atkinson 2015).

Educational Data Mining (EDM). EDM depends on computer automation (Siemens & Baker 2012). For instance, EDM researchers may apply clustering and association rule mining to adapt individualized learning experiences for users (Steiner et al., 2014). By contrast, LA researchers use statistical analysis or Social Network Analysis to inform instructors on how to help struggling students in their learning.

Adaptive Learning Analytics (ALA). Education institutions use predictive analytics to develop adaptive learning courseware, which modifies a student's learning route based on the student's interactions with the technology (Mavroudi et al., 2018). These systems rely on student data to help mimic decisions an instructor would typically make to determine the type of content, assessment, and sequence of content and assessments that will optimize learning. Using predictive analytics in adaptive learning platforms can help instructors more precisely pinpoint students' learning deficits and customize the learning experience so they are aligned with how they learn best (Ekowo & Palmer, 2016). This tool can help students accelerate their learning by allowing them to move quickly through content they already know and provide additional support in areas they have not mastered.

Predictive Analytics. Predicting learning and learning outcomes from educational data can generate new insights that benefit both the student and the teacher/instructor. Many education institutions have partnered with predictive analytics companies to improve data-informed decision-making, which impacts decision-making processes based on predictive algorithms to improve student persistence and graduation rates. According to Ekowo and Palmer (2016), the three main reasons for employing this tool are (1) to identify students most in need of advising services, (2) to develop adaptive learning courseware that personalizes learning, and (3) to manage enrollment. It is also used to help colleges determine which alumni are likely to donate to the institution and predict which student borrowers are at risk of defaulting on their loans.

Prescriptive Analytics. Higher education still faces significant challenges related to scalable and practical implementations of LA (Fritz 2016). In 2012, the Educause Center for Applied Research (ECAR) published a report on the state of analytics in higher education. Specifically, in studying interventions, the ECAR report documented a need for prescriptive analytics (intervention initiatives) among institutions (Fritz 2016) rather than relying on PA. Recommending immediate interventions instead of using assessment systems, processing the outcomes, and then reaching

Practical Applications and Implications. Advisers in adult education use LA to analyze students' success and retention. LA is also used to explore solutions that enhance students' learning and career planning by providing timely and tailored automated advice. This use of LA is exemplified by the implementation of the Degree Compass, which uses student data from previously completed courses to create predictive models and recommend which courses students should take next. Similarly, eAdvisor provides individualized support to students when they select courses and plan their degree programs. This system offers insights about viable degree pathways students may take to complete the program's core requirements. As eAdvisor assesses students' progression in a specific course, it generates timely feedback, informing students about the implications of their enrollment decisions and performance in the course toward completing their degree (e.g., expected time to graduate). The system's value was demonstrated by an increased retention of 8% in students' first year and an improvement in students' tracking in their degree programs by 69% over three years (Jarrett 2013).

2.2.4 Virtual Reality (VR) and Augmented Reality (AR)

Educators and trainers have focused on virtual reality (VR) and augmented reality (AR) as effective adult teaching and training technologies in the last decade.

Virtual Reality (VR). VR is an immersive experience and interaction with a virtual environment that is achieved by multimedia or computer-generated simulations and sensorial stimulations to help promote proactive learning in adult learners. Multiple types of devices increase users' immersion and presence by taking advantage of different senses, including sight, sound, smell, and touch (Guttentag, 2010).

Augmented Reality (AR). AR is another emerging technology that integrates real life with modified and enhanced images or sound, similar to VR technology. In AR, computer-generated images or augmentation and existing reality are harmonized to create further meanings and interactions. This is generally achieved using mobile devices to provide a composite experience or view through digital components and the real world. AR provides users enriched experiences, greater engagement, and a powerful capacity to change people's perceptions of the world. Unlike VR, AR is more easily accessible as it usually does not require wearing devices such as a head-mounted display.

Practical Applications and Implications. Understanding how VR and AR technology systems are currently used can prove insightful to adult educators. The technology was first used for military and medical purposes to provide a vivid and immersive experience in a risk-free environment (Oh et al., 2018). The examples below show VR and AR as potential learning tools to facilitate effective learning in various adult education fields.

Medical Applications. In the medical field, VR surgery is a holistic learning application that provides an uninterrupted close-up of surgical training experiences (Pulijala et al., 2017).1 Using an Oculus Rift development kit (DK2) virtual reality headset and a Leap Motion controller, this application has been utilized to demonstrate numerous surgical procedures. The three essential elements of VR surgery are a 360º experience of an operating room, close-up stereoscopic surgery visualization, and 3-D interaction. The 360-degree video creates a sense of presence in the operating room when watched on an Oculus Rift headset.

Military Applications. The military has used AR and VR to overcome the limitations of real training environments. Virtual maps and 360°-view camera imaging can improve a soldier's navigation and perspective during combat. Researchers examined the use of AR in the adaptive tutoring system so that soldiers can do hands-on applications in realistic physical environments (Oh et al., 2018).

Educational Applications. AR scenarios can be used to enrich teacher and principal preparation programs. For example, TeachLivE™ (TLE) utilizes an immersive virtual environment to provide a holistic practice environment for the aspiring teacher or principal by presenting an interactive experience blending compelling stories and characters with robust, authentic learning. Internally constructed scenario simulations engage participants in strategic learning experiences using interactive dialogue and feedback. The fact that different avatars respond differently to scenarios characterizes the authenticity of the experience (Storey & Cox, 2015). Similarly, Smith et al. (2015) used VR to effectively develop job interview training with high-functioning young adults with autism spectrum disorder (ASD).

VR and AR also provide a way to easily visualize abstract concepts (e.g., interactions between atoms and molecules in 3D virtual environments) (Blaha, 2016) and have the potential to more fully express and explore the full complexity of the human experience (Hackl, 2017). The potential applications for VR and AR are wide-ranging and can cut across multiple disciplines (Koumpouros, 2024).

3. ETHICAL IMPLICATIONS OF AI IN ADULT EDUCATION

Section 2 of this article outlined generative AI machine learning technologies being integrated into adult education, making it possible for intelligent LMS to provide adult learners with individual programs grounded on andragogically learning principles (Knowles 1980) due to AIs' ability to track and analyze student learning information in real-time. But this comes at a cost. As the transitions towards AI-driven education systems pick up pace, concerns relate to the lack of legal regulations and ethical frameworks, replication of biases resulting in discriminatory patterns, and the need to further develop a student's critical thinking skills (Akbar et al., 2024). This section of the article explores the ethical implications of AI in adult education.

3.1 AI Literacy Training

Institutional ethical dilemmas are grounded on whether to support or restrict AI generative tools (Luan et al., 2020). One advocated approach is to ensure that all learners have access to training in AI literacy supported by competencies that enable individuals to evaluate AI technologies critically. This proactive approach can prepare students to understand AI's implications and influence its ethical use (Ekowo & Palmer, 2016).

3.2 Algorithmic Bias

An increasing number of adults are using generative AI technologies in their study and work today (including adult teachers and educators) but are often unaware of the limits of generative AI technologies or need to adequately consider the risks such technologies pose from an ethical point of view. Chatbots, in particular, due to algorithmic bias, can perpetuate and amplify societal biases and unfairness, negatively impacting teaching and learning processes and outcomes. For example, if a model is trained on data biased toward specific groups of people, it may produce unfair or discriminatory results toward those groups (Kasneci et al., 2023). A digitally competent adult learner should know that ChatGPT relies on a limited database and that users should always validate the information by fact-checking and cross-referencing.

3.3 Academic Honesty

Academic dishonesty can manifest itself in many ways, including plagiarism, cheating on exams, copyright violations, and fabrication of citations and references. Institutions must counteract this tendency by developing ethical frameworks jointly led by the administration and students so that the quality of teaching and the institution's reputation are not affected (Mouta et al., 2023).

3.4 Academic Integrity

Generative AI content submitted by students to teachers/instructors challenges established norms of academic probity (Kumar, 2023), presenting educators with ethical quandaries (Tahir & Tahir, 2023). There is a constant bombardment through social media of innovative generative AI tools that assist in writing an essay, editing an essay, literature searches, and data analysis (Litero, AI Research Mode from You.com, EditGTP). The recent introduction of generative AI tools, such as Stealthgpt, promoted as undetectable by Turnitin, is particularly concerning as using this tool indicates a deliberate intent to deceive. Finally, generative AI tools such as VideoAl by Invideo provide scripting, imagery, voiceovers, subtitles, and background music for presentations grounded on the prompt given.

Rather than adapting current academic integrity and plagiarism policies, there is a need to redefine academic integrity to accommodate future generative AI tools and shift the focus from an assignment outcome to the assignment's process.

3.5 Data Privacy

Issues relating to student privacy, consent, and how data is used, managed, protected, and interpreted (Mavroudi et al., 2018) are concerns. As consumers of generative AI content and also the subject of data mining, adult learners must also be aware of the ethical implications of their actions grounded on digital skills and a solid moral compass (Ciampa et al., 2023). Students trust that institutional data is de-identified and used appropriately.

3.6 Access and Equity

According to the OECD (2021), "Artificial Intelligence (AI) has the potential to increase training participation, including among currently underrepresented groups, by lowering some of the barriers to training that people experience and by increasing motivation to train" (p.4). Certain AI solutions for training, for example, may help align training to labor market needs and reduce bias and discrimination in the workplace.

4. EMERGING TRENDS AND FUTURE DIRECTIONS

Section 3 of this article discussed the concerns and challenges of transitioning towards the broad use of AI in adult education. While Generative AI poses ethical challenges, these tools are ideally positioned to help educators transform adult education by replacing the traditional andragogical training model with a new dynamic structural model (Storey et al., 2023). This paper section focuses on emerging trends and future directions for using generative AI in adult education.

4.1 Vocational Training

The transformative role of generative AI in education, particularly in Technical and Vocational Education and Training (TVET), can reshape adult education by fundamentally changing how learning and instruction are perceived (International Vocation and Educational Training Association [IVETA] & Wawiwa Tech 2023). Through AI, educators can speedily generate course and lesson materials, immersive experiences, real-world simulations, visually striking graphics, tests, and comprehensive and personal assessments. Such enhancements are particularly valuable in vocational training and adult learning, where the application of real-world skills takes precedence.

Recent research by Akbar et al. (2024) validates IVETA's assessment regarding the significant impact of generative AI on adult education. As does a longitudinal study by Zhang et al. (2022), which monitored the professional progress of adult learners who participated in AI-driven upskilling programs. The study found that AI-driven upskilling programs substantially impacted the learners' employability and career development.

4.2 Authentic Immersive Experiences

As one of the latest technological advancements, researchers expect that VR and AR will lead many initiatives to enhance technology-embedded learning solutions for adult learners (Hummel, 2017). The immersive nature of these new technologies facilitates greater learner involvement, motivation, and absorption through more advanced features of the interactive functions of the VR and AR technologies. AIs can construct detailed rubrics aligned with course learning objectives and authentic practice-based immersive experiences.

4.3 Extended Reality (XR)

Extended reality (XR) encompasses VR and AR and embraces 3D objects, 360-degree video, VR, AR, and mixed realities (Hackl, 2017). This technology immersive method will likely become increasingly popular in adult education as XR can move seamlessly between the real and virtual worlds for improved learning (Patterson, 2016).

5. POLICY IMPLICATIONS AND RECOMMENDATIONS

The final section of this paper focuses on policy implications and recommendations for adult educators that will be necessary to develop AI-enriched adult education.

5.1 Need for Research

Educators are not known for being early adopters of new initiatives, and this is recognized by the OECD (2021), which has expressed concern that there is a lack of scientific evidence about the effectiveness of implementing AI tools into adult education compared to non-AI or human alternatives. Specifically, there is a need for research scholars to identify the VR/AR experiences that are most effective in delivering adult learning programs and how VR/AR-based learning improves adult learners' learning competencies (Ho et al., 2018).

5.2 Resource Allocation

The OECD is reluctant to allocate resources to expand the use of AI tools for teaching and training due to the need to improve understanding of AI tools and whether the benefits of the different types of tools outweigh the costs, harms, and challenges (OECD, 2021). Although there is recognition that AI can perform tasks that are traditionally human, there is an element of caution as its introduction in training would significantly change the skill requirements in jobs related to training (OECD, 2021).

Generative AI training is cost-effective as it does not require additional classrooms, teachers, or tailored curricula. This scalability can benefit employers, training providers, and policymakers (OECD, 2021). However, administrators, faculty, and instructors in adult education need to be conversant with new immersive technologies and seek effective ways of utilizing them to educate adult learners in various education settings.

CONCLUSION

Effective adult teaching and learning extends beyond the typical educational path. It is a voluntary choice of learning throughout life for personal and professional development. Traditional computer systems are being replaced by AI and integrated into adult education and adult education research (Milana et al., 2024; Kang, 2023). As the OECD noted in 2021, "Realizing AI's full potential and ensuring that using AI for training has beneficial outcomes for all requires more research and policies that address the need for digital skills, the costs of adoption, and the development" (p.9). AI has shifted the adult educator's role in adult learning by turning the learning environment into an open, intelligent learning system. Ongoing issues such as ethical concerns regarding data privacy, intellectual property, security, and cheating by learners or researchers must continue to be consistently regulated in tandem with AI's continuous development.

Adult educators must use research-based curriculum design and development in AI literacy and capabilities to further curriculum engagement and relevance. Further, AI in adult education forces adults to reflect and redefine their role in teaching, challenging them to improve their andragogical and analytic skills, develop digital literacy, and be prepared to work with AI colleagues.

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