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The effects of artificial intelligence applications in educational settings: Challenges and strategies

Omar Ali [a], Peter A. Murray [b], Mujtaba Momin [c], Yogesh K. Dwivedi [d,e,*], Tegwen Malik [f]

[a] College of Business and Entrepreneurship, Abdullah Al Salem University, Kuwait
[b] University of Southern Queensland, Toowoomba, Qld 4350, Australia
[c] College of Business Administration, American University of the Middle East, Egaila 54200, Kuwait
[d] Digital Futures for Sustainable Business & Society Research Group, School of Management, Swansea University, Bay Campus, Fabian Bay, Swansea, UK
[e] Symbiosis International (Deemed University), Pune, Maharashtra, India
[f] School of Management, Swansea University, Swansea SA1 8EN, UK

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ABSTRACT

With the continuous intervention of AI tools in the education sector, new research is required to evaluate the viability and feasibility of extant AI platforms to inform various pedagogical methods of instruction. The current manuscript explores the cumulative published literature to date in order to evaluate the key challenges that influence the implications of adopting AI models in the Education Sector. The researchers' present works both in favour and against AI-based applications within the Academic milieu. A total of 69 articles from a 618-article population was selected from diverse academic journals between 2018 and 2023. After a careful review of selected articles, the manuscript presents a classification structure based on five distinct dimensions: user, operational, environmental, technological, and ethical challenges. The current review recommends the use of ChatGPT as a complementary teaching-learning aid including the need to afford customized and optimized versions of the tool for the teaching fraternity. The study addresses an important knowledge gap as to how AI models enhance knowledge within educational settings. For instance, the review discusses interalia a range of AI-related effects on learning from the need for creative prompts, training on diverse datasets and genres, incorporation of human input and data confidentiality and elimination of bias. The study concludes by recommending strategic solutions to the emerging challenges identified while summarizing ways to encourage wider adoption of ChatGPT and other AI tools within the education sector. The insights presented in this review can act as a reference for policymakers, teachers, technology experts and stakeholders, and facilitate the means for wider adoption of ChatGPT in the Education sector more generally. Moreover, the review provides an important foundation for future research.

1. Introduction

Educational and academic practices have been exposed to significant and far-reaching technological advancements in recent times no better exemplified by the recent intervention of Artificial Intelligence (Tuomi, 2018). The swift technological research and embedded innovation in machine learning sciences has accelerated the introduction of language generation models (Dwivedi et al., 2021). This has further led to the advancement of content generation technologies and innovation pertaining to digital content development and script development using embedded AI technologies such as the ChatGPT generative model (Hu, 2023). Progression and integration of deep learning (DL) and reproducible AI technologies has led to the creation of digital artifacts and relics which systematically integrate audio-visual inputs, movable graphics and other digital and script commands. This is achieved by duly scrutinizing training inputs and synchronizing between various data patterns and designs (Abukmeil et al., 2021; Gui et al., 2023).

Contemporary published literature has acknowledged two main generative technologies: AI - Generative Adversarial Network (GAN) and Generative Pre-trained Transformer (GPT) (Vaswani et al., 2017;

* Corresponding author at: Digital Futures for Sustainable Business & Society Research Group, School of Management, Swansea University, Bay Campus, Fabian Bay, Swansea, UK.

E-mail addresses: Omar.Ali@aasu.edu.kw (O. Ali), Peter.A.Murray@unisq.edu.au (P.A. Murray), Mujtaba.Momin@aum.edu.kw (M. Momin), y.k.dwivedi@swansea.ac.uk (Y.K. Dwivedi), F.T.Malik@Swansea.ac.uk (T. Malik).

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Abukmeil et al., 2021; Brown et al., 2020; Hu, 2023; Gui et al., 2023). Presently, GAN is a GAI-enabled technology that uses dual neural networks (Karras et al., 2021). Whereas the discriminator network aids in evaluating the genuineness and authenticity of the generated content, the generator network - which is an assemblage of GPT and GAN – can generate complex data such as the graphics of a human face. This iterative verification and the corroborative protocols continue until the discriminator network can discriminate between the synthetic and real content. The synthetic is then acknowledged as genuine and authentic (Jovanović and Campbell, 2022). GAN technology is primarily reliable for generation, graphics, and video (Hu, 2023). Generative-modeling artificial intelligence (GAI) such as ChatGPT is an unmonitored or moderately monitored machine learning framework that integrates manmade content artifacts with the intervention of statistics and probabilities (Jovanović and Campbell, 2022). At its most basic however, what is completely unclear with the revelation of generative AI models is how they can be used in ways that are not only innovative, but also safe, ethical, and reliable (Jain et al., 2023). These important oversights in AI generative model innovation suggest that scholars have stopped short in reviewing the assortment of challenges that can be identified in extant research particularly within educational settings. With these facts in mind, this review paper has the following objectives. First, the authors appraise the existing literature by identifying complex patterns and challenges that remain unresolved in the science and practice of ChatGPT generative models. Second, the manuscript evaluates the *for* and *against* arguments in using AI generative models.

Generative AI models and ChatGPT in particular use Natural Language Processing (NLP) to recite and yield human-like transcripts in diverse dialects. These dialects are enabled to exhibit creative content while scripting texts. The AI platform is enabled to create voluminous content from a few lines to ballads and couplets, to a complete research article. Such content is convincing in almost all the themes that have substantial content on web–public platforms. Additionally, these models are empowered to engage clients in conversations resembling human dialogue; illustrations include customer-support chatbots or fictitious charismatic plots in computerized/electronic games (Pavlik, 2023; Rese and Tränkner, 2024). A much more erudite, better-trained, and advanced GPT-3 has been introduced recently (Brown et al., 2020). This AI version has 175 billion constraints and criteria (Cooper, 2021) wherein it can boost task-specific and objective features that can become highly efficacious through modern calibration (Brown et al., 2020). Brown et al. (2020) opined that GPT-3 is ten-fold sophisticated compared to any preceding non-sparse language model. This version is developed as the foundational NLP engine that improves the earlier language-enabled model of ChatGPT which has fascinated many diverse fields of ontology inter alia from academic education (Qu et al., 2022; Williams, 2023), to engineering (Qadir, 2022), to broadcasting and journalism (Pavlik, 2023), across different fields of medicine (García-Peñalvo et al., 2020), and in many business domains related to money transactions, finance, and economics (Fallahi et al., 2022; Alshater, 2022; Terwiesch, 2023).

Sizable language models such as GPT-3 garner substantial progressions in NLP where prototypes are proficient in processing colossal transcripts and script data that can yield texts, answers, questions, and a bouquet of script-related tasks; these outcomes are achieved with similar proficiency and intelligence of a human being (Floridi and Chiriatti, 2020). Notably, key developments in the sphere of transformer architectures and their usage (Devlin et al., 2018; Tay et al., 2023), and fundamental responsive machinery (Vaswani et al., 2017), significantly enrich the capacity of auto-regressive, self-controlled language schemas to leverage long-term adjuncts in natural-language scripts. The transformer architecture presented in GPT-3 (Vaswani et al., 2017), relies on the self-attention apparatus to resolve the consequence of the whole input mechanism while engendering prognosis. The architecture thus empowers the model to enhance the association among texts, their articulation to a context and the script, irrespective of their locus and location.

Additionally, a significant structural progress is the practice of primarily training the model system on a considerable dataset before calibrating it for a particular task. This pre-sequencing has been pivotal for enhancing the functioning of an array of linguistic syntactical functions (Hughes et al., 2016; Alzubaidi et al., 2021). Moreover, Bi-directional Encoder Representations from Transformers (BERT) is a pre-trained transformer-based encoder model commissioned on distinct and diverse NLP tasks, with capability of producing sentence cataloguing, queries, and answers and termed entity recognition (Devlin et al., 2018). Indeed, GPT-3 and ChatGPT comprise of contemporary evolutions and specific advancements where they have been instructed on much larger datasets and data availability. Advancements include scripts and amassing information from the web which have proven to be efficient on a spectrum of natural-language tasks oscillating from an array of tasks such as question-answering, to scripting comprehensive and writing essays based on the nature and peculiarity of commands received (Floridi and Chiriatti, 2020). Furthermore, contemporaneous functions have aimed at calibrating these NLP technologies on smaller datasets where transfer learning applications have been rendered to new pertinent challenges (Kasneci et al., 2023; Baidoo-Anu and Ansah, 2023).

The recent past has witnessed the advancement and adoption of large language models. However, the advancement in AI tools foregrounds the embedded challenges of these technologies (Dwivedi et al., 2023a; Dwivedi et al., 2023b; Kasneci et al., 2023; Kshetri et al., 2023; Baidoo-Anu and Ansah, 2023; Richey Jr et al., 2023). Some of these include the inability to decipher the complex and challenging nexus of predictions made by these models in the background. Further, moral contagions embody these complex systems which exhibit both predictable and unprecedented consequences across diverse contexts and industry milieus. For instance, the abuse of AI technology for immoral and unethical purposes has to be systematically anticipated and the consequences taken into consideration in model design. Taken together, such technologies will broaden the horizons, applications, relevance, and recognition of NLP. However, there has to be a systematic intervention addressing these challenges and related ethical considerations. This becomes increasingly germane when applying AI tools as learning aids for increasing know-how within relevant academic fields. Scholars suggest that consolidated and synergized research by the academic and professional fraternity is required to address such ethical and application-oriented challenges (van Dis et al., 2023). While some literature is generated in the public domain (viz. open forum posts), third party information is unreliable and unauthentic. Thus, unanimous scrutiny of the AI concept and its consequences can only be accepted when it is an outcome of empirical and systematic research deliberations. Similar to earlier language-driven models, the current review identifies a number of research gaps and challenges that need to be explored before ChatGPT users can be confident about the knowledge produced. Following a detailed and thorough review of contemporary scholarly studies, this review asks the following main research question: *What are the key challenges of harnessing ChatGPT NLP applications in the education sector and what strategies can be implemented to address them?*

The manuscript is structured as follows. Section 2 explores the background and the technological features of ChatGPT. This is followed by Section 3 where the authors outline a detailed discussion of the research methods used to conduct the review. Next, the challenges to the technology are discussed in Section 4. In Section 5, various educational strategies are identified that help to address the challenges presented. Future research directions are discussed in Section 6 including recommendations by which the scientific community can better support the progression of generative models. The limitations of the study and the conclusion to the review are discussed and outlined respectively in Section 6.

2. Related literature

2.1. Artificial intelligence overview

AI or machine intelligence is an area of computer science where machines are programmed with the ability to perform intelligent tasks that are usually undertaken by humans (Dwivedi et al., 2023c; Tsang et al., 2020; Ali et al., 2023; Pan and Nishant, 2023). Computers and machines use AI techniques to understand, analyze, and learn from data through specifically designed algorithms (Sasubilli et al., 2020; Richey Jr et al., 2023). For example, with modern AI technologies, cameras can automatically recognize faces, while computers can translate between one language to another (Sasubilli et al., 2020). AI has been founded as an academic discipline since the 1950s and since then, it has been significantly researched in areas such as NLP, learning, reasoning and various knowledge domains. More recently, AI has been transformed with the expansion of its research beyond computer science, with recent developments drawing from broad areas such as psychology, linguistics, and philosophy (Ali et al., 2023). Consequently, AI has been applied in various areas such as education, e-commerce, robotics, navigation, healthcare, agriculture, military, marketing and in gaming consoles. More specifically, widely adopted AI applications include search engines such as Google, recommender systems such as Netflix, self-driving cars such as Tesla, and human speech recognition systems such as Siri and Alexa. In general, AI methods can be broadly categorized in these areas as machine learning (Bernardini et al., 2021), robotics NLP (Murray et al., 2019), computer visioning (Jahan and Tripathi, 2021), and big data (Hossen and Karmoker, 2020).

Classification and clustering are two major techniques used in AI machine learning. Both algorithms use data such as numbers, text, images and videos, as input (Jahan and Tripathi, 2021). Classification algorithms (such as neural networks, decision trees and Bayesian networks) use huge amounts of data as training datasets. There are two types of classification algorithms: supervised and unsupervised learning (Uddin et al., 2019). Supervised learning uses labeled data vectors during training; by contrast, unsupervised learning algorithms do not use labels. Both methods use class labels during the testing phase. In machine learning, clustering algorithms are used for unsupervised learning and do not need any class label data whereas prediction algorithms are trained using historical data to develop forecasting models (Libbrecht and Noble, 2015). Several algorithms are used in classification, clustering and prediction (Elbasi et al., 2021):

AI and its sub-areas such as robotics, Internet of Things (IoTs), and machine learning can have significant impacts on society. AI technology can improve human life quality, making life easier, safer and more productive (Chaturvedi et al., 2023; Malik et al., 2021; Hradecky et al., 2022). There are several application areas of AI that make human life easier such as face recognition for security, automation for industry, NLP for translation, and robotics for homes (Herath and Mittal, 2022). AI has transformed our society to move into the Industry 4.0 revolution due to the IoTs, cloud computing, robotics, cyber physical systems and machine to machine communication (Votto et al., 2021). When used effectively, the smart automation and interconnectivity can allow people to save time, manage work flexibility and increase collaborations (Ahsan and Siddique, 2022).

2.2. Generative AI types

Generative AI can be defined as a technology that (1) leverages deep learning models to (2) generate human-like content (e.g., images, words) in response to (3) complex and varied prompts (e.g., languages, instructions, questions) (Lim et al., 2023). Generative AI models are AI platforms that generate a variety of outputs based on massive training datasets, neural networks and deep learning architecture, and prompts from users (Nirala et al., 2022). Depending on the type of generative AI model, various models can possibly generate images, translate text into image outputs and vice-versa, synthesize speech and audio, create original video content, and generate synthetic data (Porkodi et al., 2022). Although there are many different subsets and new formats of generative AI models emerging, the two primary designs are: Generative adversarial networks (GANs) and AI called transformer-based models. With generative AI, the components of the model include two different neural networks: the generator and the discriminator. The generator compiles content based on user inputs and training data while the discriminator model evaluates generated content against “real” examples to determine which output is real or accurate (Gonog and Zhou, 2019). With the transformer-based model, encoders and/or decoders are built into the platform to decode the tokens or blocks of content that have been segmented based on user inputs (Li et al., 2022).

The primary difference between generative and discriminative AI models is that the former can create new content and outputs based on their training (Qadir, 2023). Discriminative modeling, on the other hand, is primarily used to classify existing data through supervised learning (Van Engelen and Hoos, 2020). As an example, a protein classification tool would operate on a discriminative model, while a protein generator would run on a generative AI model. Generative models are designed to create something new while predictive AI models are set up to make predictions based on data that already exists. Continuing with our example above, a tool that predicts the next segment of amino acids in a protein molecule would work through a predictive AI model while a protein generator requires a generative AI model approach (Thomas et al., 2023).

In addition, another AI model Variational Autoencoders (VAE), is used for text and audio generation; VAE is a generative model that encodes data into an embedded space and then decodes it to reconstruct the original content. VAE models use distinct probabilistic combinations of input data to generate new content (Yadav et al., 2021). Similarly, Autoregressive Models (ARM) generate one-unit element at a time, deriving cues from the earlier generated element (Bai et al., 2021). This regressive one-unit at a time function aids in creating contextual and yet coherent content (GPT is one of these types). Recurrent Neural Networks (RNN) is also an AI model that processes sequential data by predicting the next unit element from the previous element; unlike ARM, they are neural networks and lack the potential to generate long sequences of data; functional improvements are currently being developed to overcome the limitations of RNN (Chen et al., 2019). Transformer-based models have raised wider acceptance since unlike RNN, they can handle long output sequences of data by creating elaborate, coherent and contextual content. Flow-based generative models have the capacity to portray the data distribution by inverting the metamorphosis between the prompt and generated output. These models aid in generating data as well as density estimation of the data generated.

It is very important to acknowledge the power of generative AI with its related concepts. In line with our definition, it is worth noting that generative AI has the unique ability to not only provide a response but also generate the content in that response, going beyond the human-like interactions in conversational AI (Lim et al., 2022). In addition, generative AI can create new responses beyond its explicit programming, whereas conversational AI typically relies on predefined responses. However, not all generative AI is conversational, and not all conversational AI lacks the ability to generate content (Lim et al., 2023). Augmented AI models, such as ChatGPT, combine both generative and conversational AI to enhance their capabilities (Dwivedi et al., 2023a). Additional background details about ChatGPT are discussed next.

2.3. Generative AI models and background to ChatGPT

Generative AI is a distinct class of AI and an incredibly powerful technology that has been popularized by ChatGPT (Lim et al., 2023). Open Artificial Intelligence (OpenAI) is the source of ChatGPT, which is a format of a large language model (Abdullah et al., 2022), which is structured to synthesize human-like text based on an array of input commands. ChatGPT is useful for a spectrum of Natural Language Processing assignments such as script generation, comprehension of those scripts and conversations, and their translation (Kirmani, 2023). The introduction of ChatGPT achieved one million users within a week of its release on November 30, 2022 (Altman, 2022; Mollman, 2022; Hu, 2023), shocking users with its degree of sophistication and human-like intelligence exhibited on specific prompts and commands. This gathered attention of social media, news and research-oriented platforms like Nature (Stokel-Walker, 2022; Metz, 2022). The technology can process multiple, complex and comprehensive tasks including drafting articles (Stokel-Walker, 2022), summarize content, sign-scripting to address distinct criteria and perform specialized functions such as drafting and de-bugging computer code. This has led to many eclectic responses from experts in academic and educational settings as the application has not only been disruptive but revolutionary in terms of its scholarly and pedagogical capacity (Williams, 2023). At its most basic, the program has dramatically increased user ability to create knowledge and the means by which it is accessed (Lucy and Bamman, 2021). As the authors discuss below however, opponents are vocal that the knowledge produced creates many ethical dilemmas thus compromising human ingenuity the quality of the teaching and learning process (Williams, 2023).

As discussed, the presence of diverse Generative AI aids in the creation of image, audio, text and visual content; this has increased the usefulness of AI to academic as well practitioners of diverse domains. That is, diverse AI tools with their embedded functional and operational utility have the latent ability to create credible content within a fraction of the time taken in traditional learning models (Kar et al., 2023). They can also be customized to initiate sequential prompts. While current Generative AI aids may look revolutionary, their origin can be attributed to the 1960s when Chatbots were invented. Mostly, AI models became invasive around 2014 with the inception of GANs, which is a typology for machine learning algorithms (Behrad and Abadeh, 2022). This breakthrough technology and its application in diverse fields has led to its application and adoption in a variety of technical, intellectual, business and operational contexts e.g., the movie industry and in academic writing inter alia. Transformer technology which is based on machine learning has revolutionized learning by enabling the training of AI models to embed colossal content without the necessity to label the content in advance. These transformer aid models create a nexus of prompts across, pages, data-sets, books and input chapters, compared to their predecessors who were restricted to searching for sentences and words. Thus, AI models have the ability to revolutionize nascent fields like Biotechnology for instance since they can create connections across bio-codes, bio-chemicals, proteins and DNA strands. Large Language Models, of which ChatGPT is a type, have unearthed a plethora of generative AI models that can create images, audio and visual content from trivial prompts (Kumar, 2023).

ChatGPT materializes a transformer architecture, a computer-enabled neural nexus that accentuates the NLP abilities of an artificial system. This architecture is connected to a large input data-set and is integrated to devise transcripts based on its data source though creative blending (Baidoo-Anu and Ansah, 2023). The input command of the application processes and furnishes an output for each unit of transcript as one-unit time. The whole output is attached to the preceding unit-output in the string in connection with the linkage prompt/command that was rendered. The application materializes attention machinery to focus on the maximum segment of the input to produce an output that is intelligent, comprehensive and customized to the input received. ChatGPT can be seasoned and made comprehensive on specialized actions like contextual dialogue-generation or query-resolution systems by offering an additional command of task-specific input by improvising it for the specific NLP application. The mechanism can be configured for distinct dialects and vernaculars by customizing the input datasets or by prototyping it with specific language computer codes (Kasneci et al., 2023).

The COVID-19 epidemic has been disruptive highly disruptive in educational setting in relation to how educational content was delivered with most major academic institutions transitioning to electronic, remote, and online learning, to conform to social distancing guidelines (Chatzipanagiotou and Katsarou, 2023). Significant change to this extent was a disruptive shift to digital and online pedagogy, as institutions and the international community mandated quick adoption of the technology-enabled teaching-learning process in the face of increasing adversity (Coghlan et al., 2021; Henderson et al., 2022). The pandemic had effectively curtailed the face-to-face learning system meaning a major transition and unprecedented embrace of technology were required in the teaching-learning space. This has included the acceptance of online virtual conversational platforms such as Google Classroom, Teams, Zoom, and other different video tools (e.g. online conferences) which extended to other pedagogical tools like e-books, videos, and interactive activities (Chatzipanagiotou and Katsarou, 2023). Use of sophisticated learning management systems like Moodle, Google Suite, has further empowered the teaching-learning fraternity with new teaching aids. Thus, the advent of different e-learning platforms has revolutionized the delivery of education which has had to become more agile to invite the participation of students including remotely.

Moreover, the global pandemic invited the need for more self-dependence and asynchronous learning systems. Here, learners now require substantial independence in how they learn and the speed by which they learn. Artificial intelligence and generative models such as ChatGPT accounts for the new requirements and convenience of learning and at least in theory, can embody a learner's socio-cultural background. However, this AI transition has magnified many pedagogical issues related to quality including the digital divide between those who have access to sophisticated technology and those who don't (Cain, 2023). Generative AI models have brought to the surface other drawbacks as well such as restricted interaction, a dearth of academic readiness, and issues of ethics and poor accountability (Baidoo-Anu and Ansah, 2023; Nguyen et al., 2023; Yan et al., 2023; Stahl and Eke, 2024). Holistically, the pandemic catalyzed the adoption of technology in education while underscoring problems of learner-inclusivity and accessibility (Chatzipanagiotou and Katsarou, 2023). These facts have brought a greater focus on global education systems. For instance, the education system is invested with the responsibility to perennially adapt, evolve and bridge the gap between the stakeholder (student, teachers, and parents) needs during challenging times (Schiff, 2021), yet many challenges remain in adopting generative AI models such as ChatGPT within educational settings more generally.

While these advancements may seem to be 'breakthroughs', generative AI is still in a nascent stage. Similar to any breakthrough technology, the introduction of AI models embodies many biases, data accuracy problems, cognitive hallucinations and failures. While the progression of AI has the potential to revolutionize many diverse fields of ontology such as in educational settings and in research domains more generally, managing the quality of outputs remains a work in progress given how generative models can create chatbots, deep fakes, movie dubbing, scripting emails/formal content, creation of art/videos and others.

In summary, the introduction of ChatGPT grew remarkedly at the juncture of the receding pandemic with its innovative features advanced quickly into many industry and related fields such as in education settings. However, as the technology has evolved, many new challenges and ethical anomalies can now be identified bringing to the forefront emerging paradoxes that are not easily solved. Our discussions thus far suggest that generative AI tools are disruptive yet represent a transformative technological intervention. However, generative AI tools such as ChatGPT are currently being debated and scientifically explored as technology experts and advanced users consider ways that it can be universally adopted. In what follows, the authors delve into the key challenges that threaten its adoption with the discussions focused mainly on the education sector.

3. Research methodology

Watson (2015) and Ali et al. (2018) were the seminal papers in the area for conducting systematic and scoping reviews. Here, the protocols and processes for identifying, selecting, and evaluating the literature have been established bringing to light the relevance of specific research parameters. Here, the researchers have carefully constructed the review process in such a way that it is highly resourceful (Tranfield et al., 2003), systematic, independent and rigorous (Boell and Cecez-Kecmanovic, 2015). Following the reviews of Kitchenham and Charters (2007) and Ali et al. (2018; 2020b), the current manuscript flows through the stages of planning, execution, and summarizing where a detailed explanation is next outlined.

3.1. Planning stage

First, a planning stage consolidates the need for a review and a study of this magnitude for the development of an area of discipline. Despite studies on critical challenges in using ChatGPT, academic investigations and systematic reviews about this generative AI tool have been underdeveloped. Consequently, the current paper entails a comprehensive investigation into the existing literature and information of the effects of generative AI and ChatGPT extant research and practice. Second, the planning stage enabled the researchers to identify the research question: *What are the key challenges of harnessing ChatGPT NLP applications in the education sector and what strategies can be implemented to address them??*

The researchers augmented the automated search strategy with a manual intelligible review process. The initial stage included a search-engine automated exploration in diverse electronic data bases and repositories. Subsequently, a manual analysis of assorted publications was made (Golder et al., 2014). Based on research terms, the researchers scanned Science Direct, Web of Science, IEEE, Emerald, Scopus, and ACM digital library to collect relevant data for the review process. Moreover, a systematic assemblage of methods were used to filter and restrict non-relevant research publications (McLean and Antony, 2014). The manual process required the researchers to read each article's title and abstract (Golder et al., 2014), followed by a complete reading of the article to ascertain its relevance to the scope of research outlined across the key themes (Ali et al., 2018). More details are represented in Table 1.

Table 1
Stages of article selection and results.

Stage	Actions	Result
Stage 1: Search the literature using specific terms or keywords	**Identification of search keywords:** • Challenges • Strategies • ChatGPT • AI • Education sector	618
Stage 2: Applied filtering tools within the database	**Apply database filters:** • Language • Year of publication • Area of Study	233
Stage 3: Exclusion of articles based on their title and abstract	**Reading title and abstract** • Review the title. • Review the abstract	124
Stage 4: Exclusion of articles based on full-text review	**Reading full articles** • Review the whole article	87
Stage 5: Exclusion of articles based on their quality	**Quality evaluation:** • Research objectives • Research questions • Research problem • Research Data used • Adopted study methodology • Research results and outcomes	69
Total Articles Accepted (based on the 5 stages)		69

The review protocol served as a foundation for developing both practical and theoretical views on generative AI models. The process then led to a review of an initial content classification model (Ngai and Wat, 2002) where articles were clustered and catalogued and a framework developed. The structure entailed the process of packeting research themes and identifying crucial aspects of the key challenges of using ChatGPT in the education sector. For instance, many key challenges started to emerge from the process such as poor human-AI interface, restricted understanding, bias in training input-data, the stifling of creativity, data privacy and security, cost of training and maintenance, and sustainable usage. Each of these challenges is detailed later in this review.

3.2. Execution stage

For this phase, the planning phase was used to filter relevant articles for the three-stage review process. The methodology sequenced for the review study included: (1) identifying the search terms and text in a perineal format which delved into using exclusive and distinctive technical terms recognized in the sphere of research (Hu and Bai, 2014). The keywords identified were: (“challenge(s)” OR “issue(s)” OR “barrier (s)” OR “obstacle(s)” OR “consideration(s)”) AND (“ChatGPT” OR “AI” OR “NLP”) AND (“education” OR “university” OR “school”); (2) The database was further scrutinized by filtering tools to enhance the relevance of search yield with a temporal constraint between 2018 and 2023 (Zhang et al., 2014); (3) Following this, the manual check included scanning the title and abstract to further specify the configuration of the results (Pucher et al., 2013); (4) Articles screened in Stage 3 underwent detailed analysis comprising reading the full-text article where the researchers filtered and distinguished between relevant knowledge, information, and theory related to the discipline under investigation (Shea et al., 2007); (5) Finally, a Quality assessment standard was applied to ensure that all the research articles screened up to and including stage 4 were relevant and contributed to the formulation of this review manuscript (Hu and Bai, 2014). The quality evaluation comprised of creation and acceptance of Quality evaluation criteria to warrant that the screened papers qualified for the minimum quality standard (Hu and Bai, 2014). Taken together, the criteria that was adapted from Sadoughi et al. (2020), and Ali et al. (2018, 2021) included: (1) A statement of research objectives, (2) that the embedded research questions and challenges were stated sequentially, (3) Review data was described and made available, (4) that a comprehensive description of research method, and substantial explanation of its presentation and execution was available, (5) and that the research outcome was relevant to the research questions. Comprehensive details of the research article selection stage and the results are illustrated in Table 1.

3.3. Summarizing stage

The review was undertaken between February 2nd 2023, to April 3rd 2023, following the sequence and stages represented in Stage 1. The preliminary database search yielded a total of 618 articles. Following the review process however, a total of 69 articles were only considered for the review as illustrated in Table 2.

Fig. 1 illustrates the final number of articles selected for the present review study. Specifically, based on the initial search process (keywords), 618 unique articles were identified. After applying filters, the number of articles was reduced to 233 articles. The researchers then conducted a manual review to identify articles irrelevant to the study. In this process, the researchers focused on both empirical and conceptual articles that were directly related to the topic of this research. As a result, 109 articles were removed, and 124 articles remained. Next, the full article reviewing process was performed. After reading and reviewing the full articles, another 37 irrelevant articles were removed, which

Table 2
Categorization framework.

Domain	Category	Sub-category	Description	Examples	Sources
ChatGPT Challenges	User Challenges	Absence of human interaction	The lack of human interaction during the use of such an AI platform renders the user experience excessively mundane and mechanical.	• Increasing use of technology • Decrease in face-to-face communication • Lack of social interaction	Gong et al. (2018); Rapanta et al. (2020): Baber (2021a, 2021b); Gao (2021); Bernius et al. (2022); Diederich et al. (2022); Kasneci et al. (2023).
		Restrained understanding	This AI-based assistance tool works on the data that it has been trained on and that might lead to its limited understanding of the contexts being discussed.	• Difficulty in understanding natural language • Limitation in content knowledge	Perelman (2020); Wang et al. (2020); Buhalis and Volchek (2021); Bernius et al. (2022); Omoge et al. (2022); Raković et al. (2022); Kim et al. (2022); Sheth et al. (2022); Kasneci et al. (2023); Baidoo-Anu and Ansah (2023).
		Little creativity	The absence of imaginative stimulus owing to the nature of this tool manifests in an explicit lack of creativity.	• Limitations in learning approaches • Lack of novelty • Potential for overreliance	Pappas and Giannakos (2021); Chen and Wen (2021) Xia (2021); Stevenson et al. (2022); Placed et al. (2022); Kasneci et al. (2023); Biswas (2023); O'Connor (2023); Lund et al. (2023).
		Restrained contextual understanding	The data fed into ChatGPT is collated from a wide variety of sources and hence may lack contextual background.	• Ambiguity in language • Lack of background knowledge • Inability to interpret non-verbal cues • Limited ability to adapt to new contexts	Niño (2020); Simkute et al. (2021); Miao and Wu (2021); Liu et al. (2021); Diederich et al. (2022); Atlas (2023); Floridi (2023); Dwivedi et al. (2023a); Kasneci et al. (2023).
	Operational Challenges	Cost of training the model	The success of this AI tool is dependent on its recency and training, the perennial need for such training data can be an expensive input.	• Expertise • Training data • Computational resources • Ongoing maintenance	Chen et al. (2020); Okonkwo and Ade-Ibijola (2021); Hu (2021); Bogina et al. (2022); Dwivedi et al. (2023a); Kasneci et al. (2023).
		Cost of Maintenance	The data used by large language models has to be regularly updated and vetted for accuracy. Such data maintenance tasks are also high-cost tasks	• Technical maintenance • Data • User Feedback • Model re-training	Gao (2021); Bernius et al. (2022); Haleem et al. (2022); Agomuoh and Larsen (2023); Kasneci et al. (2023); Baidoo-Anu and Ansah (2023); Sigalov and Nachmias (2023); Polak and Morgan (2023).
		Inadequate ability to personalize instruction	ChatGPT in its present form appears to lack personalization and adequate customization options. However, ChatGPT will become more customizable in the near future.	• Limited information about student • Inability to provide feedback • Limited flexibility • Limited interactivity	Dehouche (2021); Gao (2021); Ahsan et al. (2022); Kasneci et al. (2023); Baidoo-Anu and Ansah (2023); Eysenbach (2023); Gilson et al. (2023); Cotton et al. (2023); Kasneci et al. (2023).
	Environmental Challenges	Sustainable usage	The growing popularity of this large language model creates the need for huge computing and processing capacity. The need for servers and processors for this purpose poses a new challenge to sustainable computing.	• Energy consumption	Patterson et al. (2021); Kasneci et al. (2023).
	Technological Challenges	Data privacy	Since ChatGPT is gaining popularity as a ‘go-to’ solution for a wide variety of problems from content generation to coding, users are required to share details that may potentially compromise their privacy.	• Data breaches • Privacy policies • Consent • Data collection and use	Bundy et al. (2019); Breidbach and Maglio (2020); Williamson and Eynon (2020); Stahl (2021); Okonkwo and Ade-Ibijola (2021); Belk (2021); Irons and Crick (2022); Selwyn (2022); Dwivedi et al. (2023a); Kasneci et al. (2023).
		Data security	With the exponential growth of its user base, this AI platform is likely to attract the attention of malicious players seeking to benefit from the vulnerabilities in the system.	• Cyberattacks • Compliance • Data storage • Authentication	Geko and Tjoa (2018); Okonkwo and Ade-Ibijola (2021); Stahl (2021); Deng and Lin (2023); Dwivedi et al. (2023a); Kasneci et al. (2023).

(*continued on next page*)

Table 2 (*continued*)

Domain	Category	Sub-category	Description	Examples	Sources
		Dependency on data	This AI-based tool is dependent on the data being fed to the model and hence it is constrained by this dependence.	• Quality of data • Limitations in training data • Ongoing training • Potential for overfitting	Sarker (2021); Shen et al. (2021); Asselman et al. (2021); Ouyang et al. (2022); Tlili et al. (2023); Dwivedi et al. (2023a); Kasneci et al. (2023).
	Ethical Challenges	Partiality in training data	Since this large language model is founded from the input-data sourced from the internet, a lot of prevailing bias makes its way into ChatGPT. This bias is further perpetuated through the responses and solutions shared by ChatGPT.	• Reinforcing stereotypes • Lack of diversity	Akter et al. (2021); Potts et al. (2021); Stahl (2021); Bender et al. (2021); Böhm et al. (2022); Yang (2022); Chen et al. (2023); Weissglass (2022); Hamilton (2022); Heikkilä (2023); Bjork (2023); Kasneci et al. (2023); Hartmann et al. (2023); Krügel et al. (2023); Dwivedi et al. (2023a); Getahun (2023); Chin et al. (2023).

resulted in 87 remaining articles. Finally, after checking the quality assessment criteria such as objectives, the research questions, the description of the collected data, the methodology applied, the technique used to analyze the data and the presentation of the results, 18 articles were removed, reducing the number of articles to 69.

3.3.1. *Article distribution by publication year*

Fig. 2 depicts the total number of selected publications scanned in this review analysis over the years. This review study discovered that the most articles were published between 2021 and 2023 with 21 articles, while the fewest were published in 2019, with only one article. The majority of the publications were sourced from 2021 to 2023, indicating more recent interest.

The results of a comprehensive examination of the challenges of using ChatGPT in education and scientific related journal papers were presented and discussed. The categorization framework was used with five categories considered: user, operational, environmental, technological, and ethical concerns. The systematic process enabled the emergence of the most important challenges of adopting and using any of the innovation tools provided in ChatGPT. Table 2 also illustrates the results of the review by key themes and a comprehensive research framework that can be used for exploring the challenges presented.

In summary, the researchers conducted a categorical and systematic selection of research methods in the current study by reviewing, collecting, cataloguing and describing the major themes investigation. The review now breaks down each of the broad challenges by a granular discussion of the more specific challenges and barriers.

4. ChatGPT key challenges discussion

While many benefits appear on the surface level for education institutions, many downsides and potential challenges need to be addressed. This review now addresses each of the themes that were identified in Table 2 categorization framework.

4.1. *User challenges*

4.1.1. *Absence of human interaction*

While ChatGPT has harnessed worldwide interest, certain challenges have to be addressed such as the lack of humane interaction (Diederich et al., 2022; Kasneci et al., 2023). Applications such as generative AI models and ChatGPT lack adeptness in rendering human interaction comparable to language models. They do not accommodate the idea of a *humane* instructor. Increasing use of technological applications particularly AI represents a significant concern in all education institutions. While the presence of technology has revolutionized the way learning is imparted and information is accessed, it has not been mindful of the value of in-person communiqué and collaboration benefits which is central to a well-versed learning system. The seminal works of Rapanta et al. (2020) found that pupils who received personalized human feedback and support from instructors exhibited superior educational accomplishments and engagement in the teaching-learning process, relative to those who relied on automated, digitized academic programs and nodes (Gao, 2021; Bernius et al., 2022). That is, an important understanding of technology intervention in humane disciplines is the human interaction component which is pivotal in the learning process. Baber (2021a, 2021b) found that learning aspirants in an online course received inferior results relative to their peers who participated in the same course in a traditional classroom. This would suggest the need to engage learners in a holistic learning process highlighting the need for greater collaborative learning and social interaction experiences. In the era of educational digitization, concerns like these have become a focal concern for educators across the globe (Kasneci et al., 2023). Similarly, Gong et al. (2018) found that blended learning environments i.e. combining face-to-face and online learning, led to greater commitment and academic gratification among participants compared to learners

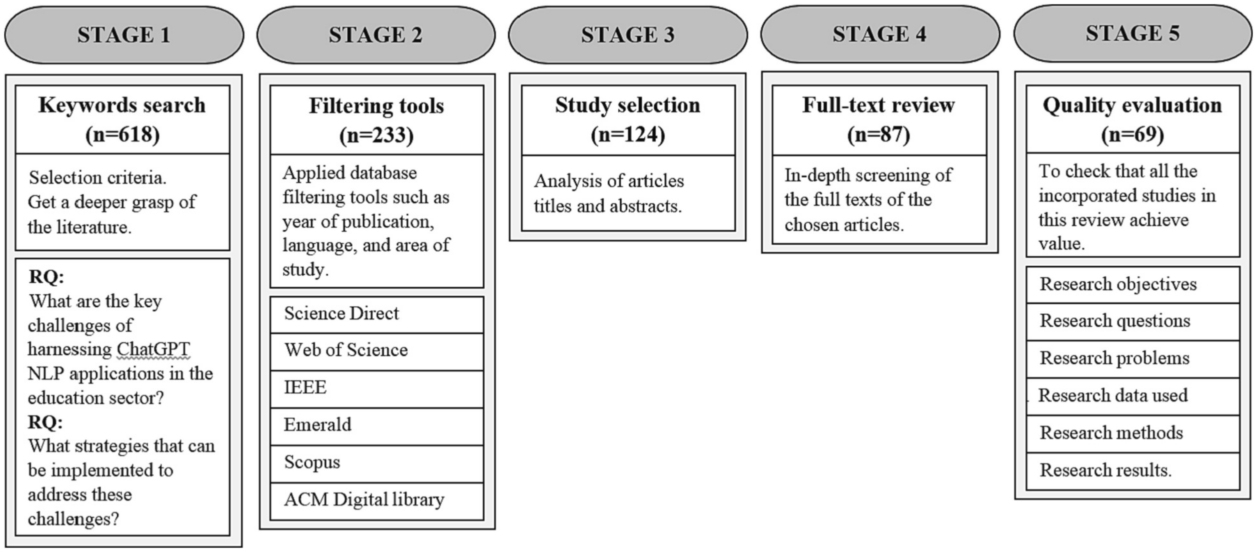

Fig. 1. Research process of this review

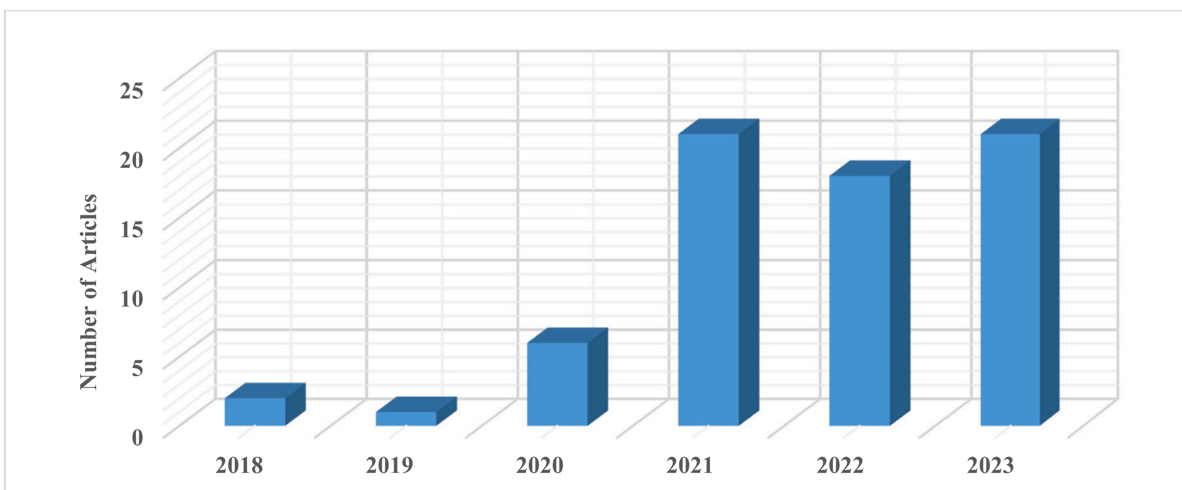

Fig. 2. Publications by year.

who relied on technology alone. Moreover, much research attributes academic excellence to personalized coaching and a blended learning atmosphere much less learning restricted to computer interactions (Bernius et al., 2022). Much research suggests the need for increased social engagement on the part of the learner in education settings (Rapanta et al., 2020). While technology can facilitate the educational journey and harness information as a support function, it cannot substitute for personalized tuition and human interaction in the teaching-learning process (Diederich et al., 2022).

4.1.2. Restrained understanding

According to extant research, statistical patterns in data on which an AI application is trained is fundamental to Generative model functioning. That is, generative models are completely ignorant of the knowledge concepts they are helping students with (Perelman, 2020; Kasneci et al., 2023). Ideally, a knowledge generative model should be very specific to student's needs and aspirations (Wang et al., 2020; Bernius et al., 2022; Baidoo-Anu and Ansah, 2023). Thus, these structures should have the intelligence to sense individual specific needs and deliver outputs accordingly. Recent studies suggest that generative model-based instruction requires greater sophistication to be able to rationalize bespoke students' needs and knowledge requests (Kasneci et al., 2023). Some challenges associated with limited understanding in education settings are as follows: (1) *Difficulty in understanding natural language*: As ChatGPT is structured and has the restricted capacity to understand NLP to decode and generate human language output, the current technology is not yet sophisticated to commensurately shuttle between natural and human language and share specific outputs (Buhalis and Volchek, 2021; Omoge et al., 2022). Thus, instances have been reported where ChatGPT misconstrues or fails to comprehend students' inquiries influencing output quality (Kasneci et al., 2023). Moreover, an ill-informed answer may render the response perplexing and create confusion on the part of students, while diminishing the power of technology in the academic sphere (Raković et al., 2022). (2) *Limitations in content knowledge*: While ChatGPT can engender unlimited replies, there is an embedded fundamental issue of limited access to trained data/content, which restricts the quality of outputs received. This is particularly more germane on parameters of novelty such that an incorrect output is offered to students in a relatively unexplored domain or gamut of study (Kim et al., 2022). In addition, while ChatGPT can engender custom-made learning content and answer queries (in this case, those generated by students), it is currently incapable of offering personalized encouragement and consideration to individualized needs in the same way as traditional education settings (Sheth et al., 2022).

4.1.3. Little creativity

One of the significant challenges faced by the ChatGPT relates to the lack of innovative output quality (Lund et al., 2023; Kasneci et al., 2023). This is largely due to the single source of training data input that the mechanism has received. Generative models rely on the input training data source, and although they modulate the patterns of output, they systematically generate monotonous and non-creative content. This curtails the innovation and uniqueness of replies (Pappas and Giannakos, 2021; Biswas, 2023). Chen and Wen (2021) moreover established that a generative model-based tune composition system had a regulated capability to produce unprecedented, novel and distinct tunes. While some creativity can be observed within limited contexts therefore, significant drawbacks such as plagiarism and violation of copyrights restricts the unique aspect of creative content. While ChatGPT can be fine-tuned and personalized to configure specific learning content and answer student queries, it is incapable of dealing with resourceful and ingenious problem-solving contexts such as critical thinking which is a pre-requisite in the education system (Kasneci et al., 2023). Several other challenges also need be noted as follows: (1) *Limitations in learning approaches*: ChatGPT spawns responses based on the restrictive training data rendered. While it can respond to forthright questions, it cannot deal with contextual problem solving, innovation, and establishing a critical mindset such that it might help students find creative solutions (Mantelero, 2018; Kasneci et al., 2023). (2) *Lack of novelty*: Input and training data are the primary sources of ChatGPT responses; thus, expecting unprecedented, innovative solutions to unprecedented queries is most likely a distal expectation (Xia, 2021; O'Connor, 2023) among learners. (3) *Potential for overreliance*: Generative AI could be expected to impair student's self-dependence. Given that it is easy for a learner to access the application, a sense of overreliance may inhibit learner self-dependence and creative ways of problem-solving and lateral thinking (Stevenson et al., 2022; Placed et al., 2022).

4.1.4. Dependency on data

Yet another detriment to the use of ChatGPT is its dependence on data archives and primordial data (Tlili et al., 2023; Dwivedi et al., 2023a). Applications like these that are generative in nature, are trained on significant amounts of input data and are highly dependent on the compilation of data to maintain quality (Kasneci et al., 2023). If the content is insufficient as far as quantity or quality, then this means that the output reproduced will be deficient in some way. Roumeliotis and Tselikas (2012) suggested that such a generative model-based query-response mechanism accomplished poor responses when the input training content lacked relevance to the context and nature of the task, for which the content had to be generated. Thus, ChatGPT mandates enormous sets of data to train the model. Further, the accuracy and effectiveness of such input data has to be contemplated. Input from an unauthentic and unverified source may influence the quality of data output. Some of the challenges associated with dependency on data in ChatGPT are discussed as follows: (1) *Quality of data*: The efficiency of the application in question is heavily dependent on the accuracy of the responses generated as an output. If the input content is inaccurate, incomplete, or prejudiced, it can lead to incongruous and inappropriate output. A study by Shen et al. (2021) for instance found that models trained on low-quality data can results in significant deterioration of output quality and thus question the whole performance of generative AI models and their applications. Thus, the data source needs to be well-researched, substantiated, and authentic. Without this, any future data generated through ChatGPT will result in another genre of biased, unauthentic data. This might spawn a chain reaction of the unverified data string leading to inaccurate output significantly influencing the quality of knowledge in educational settings. (2) *Limitations in training data*: With the paucity of data on certain knowledge parameters a distinct possibility, the inefficiency of the applications can surface. This may lead at its most basic to questions of accuracy resulting in a lack of and comprehensive understanding bringing in to question the mission of education (Tlili et al., 2023). Further, generative models have embedded challenges of generating the same nature of data demanded on the input and a lack of incorrect output related to the novel and unexplored themes. (3) *Ongoing training*: To keep the application relevant, it needs to replenish itself with content revision and training data as an intermittent function. This could be perplexing as the timely availability of novel data in palatable formats may require colossal infrastructure to collect and process the data (Ouyang et al., 2022). Moreover, depending on others for the creation of data and labelling it as 'training' data for the generative system is a tricky task to address. (4) *Potential for overfitting*: A so called efficient generative AI model runs the risk of being so befitting to specific training data within a context that it limits its usability thus restricting its capacity to be categorized and theorized to varied and newer contexts (Asselman et al., 2021). Thus, its relevance to the academic stream is questionable requiring greater substantiation through new research. Further, these regenerative mechanisms need a continuous flow of input data from parallel–specialized fields of ontology (Kasneci et al., 2023). This may need significant investments in to the future and the creation of infrastructure that might be established in a parallel economy.

4.1.5. Categorical, contextual comprehension

Contextuality and application-orientation are pivotal to different fields of education with many academic the disciplines solely dependent on application-oriented computer applications, management studies, astrophysics, *interalia*. In the absence of applying AI generative models to fit specific academic disciplines and fields of ontology, significant challenges remain how best to use AI (Kasneci et al., 2023). Generative models have an inherent challenge of not being receptive and sensitive to contexts which can completely make the content incongruent, irrelevant and thus unusable. Taken together, the contextualization of content, poor human interaction, a lack of interface, and continuous quality data input intervention compromises the quality of ChatGPT in the educational field (Diederich et al., 2022). For instance, Miao and Wu (2021) and Liu et al. (2021) suggest that a generative model-based input conversational system has an embedded limitation on interpreting the context and its suitability to an input string. As the technology is relatively novel, the absence of requisite skills for data redemption by teachers can lead to significant and newer challenges especially in the context of education.

The application has the embedded issue of contextualizing the input question which may lead to inaccurate, irrelevant, and confusing responses restricting its usability. Some of the challenges associated with the lack of contextual understanding in ChatGPT are discussed as follows: (1) *Ambiguity in language*: The use of natural language can be ambiguous to a computing device, as the coder of the input content is human and the contextuality has an integral role to play in modulating the nature of output expected. ChatGPT may not be able to precisely construe the milieu of a query cascading as irrelevant or inappropriate responses. That is, if not interpreted correctly with due consideration, the knowledge generated may bring in to question the whole regenerative process. For instance, Niño (2020) established that contextual misunderstandings in Machine learning, translation, and interpretation can translate as errors in output quality. (2) *Lack of background knowledge*: Differences in background knowledge/input data between ChatGPT and human tutors can juxtapose the inability of generative models to provide exact, authentic, reliable, and complete replies to scholarly queries (Simkute et al., 2021). The mechanistic and non-human understanding of the language model can lead to ambiguous, confusing, and irrelevant mining of data which may mostly be inadequate for teaching-learning quality. (3) *Inability to interpret non-verbal cues*: The inability of generative models to recognize non-verbal cues such as facial expressions or tone of voice, can impair it from recognizing the meaning and contextuality of the input (Kasneci et al., 2023); thus, an output void of emotions and human feelings may not be palatable in every scenario.

4.2. Operational challenges

4.2.1. Cost of training methods

The adoption of large language and generative technologies may create infrastructure and economic burdens for educational institutions particularly those with restricted financial resources (Kasneci et al., 2023). Moreover, the application model necessitates momentous computational resources and specialized expertise which may not be feasible for these institutions. Particular issues can be categorized as follows: (1) *Computational resources*: Coaching issues will consume significant computational infrastructure i.e., processing power, speed, memory, storage, security which may be a significant drawback for low-budget and unfunded/under-funded educational institutions (Okonkwo and Ade-Ibijola, 2021). This reality brings to the forefront problems of universal AI adoption. (2) *Expertise*: Developing the AI model requires expertise in NLP, machine learning, and data science, meaning finding expert intelligence is expensive (Hu, 2021). (3) *Training data*: As discussed earlier, the input training data is fundamental to the functioning of ChatGPT which if derived from quality sources can be expensive to acquire and maintain. Investments will be required in data collection, annotation, and curation as well as in the development of tools and processes for managing training data (Bogina et al., 2022).

4.2.2. Maintenance costs

Ongoing maintenance and debugging are a necessity for this dynamic generative model (Agomuoh and Larsen, 2023). Once the model is deployed, continued maintenance is required for optimal performance. Some of the challenges associated with the cost of maintenance in ChatGPT include: (1) *Technical maintenance*: The model requires ongoing maintenance especially software updates, bug fixes, performance, and optimization issues. This could be expensive and time consuming and depend on technical know-how which may not exist in some institutions (Baidoo-Anu and Ansah, 2023). (2) *Data maintenance*: The AI model requires continuous data maintenance such as data cleaning, data annotation, and data quality monitoring. Thus, technical maintenance costs could be exorbitant within specific educational settings (Sigalov and Nachmias, 2023). (3) *User feedback*: User feedback is an integral input for the modulation of the application (Bernius et al., 2022) which might also be expensive and time-consuming in the initial years of its introduction (Gao, 2021). This challenge could be escalated with the number of licensed users of the application and the complexity of the educational setting (Haleem et al., 2022; Baidoo-Anu and Ansah, 2023). (4) *Model retraining*: Given the pace of knowledge renewal in the 21st century, data input and output can become redundant very quickly suggesting that to maintain the precision of the model, it has to be updated and timely retrained by discarding obsolete parameters while onboarding new ones. This can be economically inefficient and time-consuming particularly for large and complex models (Polak and Morgan, 2023).

4.2.3. Instructional input personalization

A fundamental challenge for AI generative model applications in the academic sphere is the restricted ability to personalize commands and instructions (Kasneci et al., 2023). That is, generative models cannot interpret personalized instructions/commands to cater for individuals' needs (Baidoo-Anu and Ansah, 2023; Eysenbach, 2023), as the machine-driven mechanisms are not equipped to render customized services. As ChatGPT cannot cater to the personalized learning needs and experiences of each pupil, its effectiveness as an educational tool is questionable. Some of the encounters associated with the limited ability to personalize instructions in ChatGPT include: (1) *Limited information about students*: In the absence of granular information concerning student needs such as learning formats, interests, and preferences, including strengths and challenges, the capacity of the application to offer a holistic and wholesome learning experience is ambiguous and questionable. In these circumstances, ChatGPTs usability for 'personalized' learning experience and student inclusivity is under question (Eysenbach, 2023). (2) *Inability to provide feedback*: ChatGPT cannot harness feedback that is customized to individual learning needs within a context meaning that the AI tool is not currently viable for many educational institutions and their constituents (Gao, 2021). Comprehensively, it fails to offer individualized feedback to students' learning methods and challenges (Ahsan et al., 2022; Baidoo-Anu and Ansah, 2023), which currently can only be offered by a human tutor. (3) *Limited flexibility*: AI tools more generally fail to synergize the ever-transitioning needs of student cohorts and their latent learning needs further diminishing their capacity to offer personalized learning experiences customized to individual students' distinctive learning aspirations (Gilson et al., 2023; Cotton et al., 2023). (4) *Limited interactivity*: Personalized learning experiences with the social and interactive nature of learning are limited and questioned (Dehouche, 2021; Kasneci et al., 2023).

4.3. Environmental challenges

4.3.1. Sustainable usage

The sustainability and ongoing usage of this application/model in the education sector is a very real question for end-users (Kasneci et al., 2023). High energy consumption, infrastructure maintenance, and environmental deterioration represent critical objections that need to be addressed. Thus, energy-efficient infrastructure and collaborated storage (e.g., cloud), powered by renewable and eco-friendly energy sources are required for their ecologically sustainable operations in education settings (Patterson et al., 2021). With the evolution of environmental consciousness and the human development index, the fact that technological advancement is taken as a deterrent to the environment is a given. For instance, one of the significant reasons for the tardy adoption of Bitcoin is its significant effect on the environment and mother earth suggesting the ChatGPT developers need to find ways to reduce its carbon footprint (Kasneci et al., 2023). For its continuous use in the education sector, consolidated efforts of teachers, institutions, policymakers, and administrators should be aimed at reducing the immediate and long-term impact of this technology on ecological and environmental grounds. The actions have to be aimed at maintaining the application and its technical derivatives for their sustained and ethical implications in the classroom (Kasneci et al., 2023).

4.4. Technological challenges

4.4.1. Data privacy

Another significant challenge is the privacy of pupil information (Irons and Crick, 2022). These include: (1) *Data breaches*: Student data stored in insecure data connections, or servers can escalate the threat of unauthorized access (Kasneci et al., 2023; Williamson et al., 2020); which may also increase the threat of crimes and data forgery, plagiarism, and copyright violation. Further, plagiarism and copyright violation are yet another significant challenge that educational institutions will need to address before the application is adopted in mainstream educational settings. (2) *Privacy policies*: Proliferation of the use of ChatGPT in education may mandate policy shifts to foster ease of use and address embedded challenges with generative technologies. This can be time-consuming and challenging, especially in contexts wherein there is a regulatory and policy vacuum (Williamson and Eynon, 2020). (3) *Consent*: In continuation with the previous element, the adoption of ChatGPT in academia may need informed consent of parents and their wards depending on their age, to comply with regulations and privacy laws (Stahl, 2021). In situations where a student is not old enough, gaining careful consent from guardians will also be a significant challenge (Selwyn, 2022). (4) *Data collection and use*: The dual process of monitoring data usage and data access particularly for educational institutions may lead to information breaches, data collection transparency, and embedded technical issues (Kasneci et al., 2023).

4.4.2. Data security

Data security closely follows data privacy. Data security is an embedded problem within education settings (Okonkwo and Ade-Ibijola, 2021; Dwivedi et al., 2023a), since data breaches are subject to fraudulent individuals and groups. Here, problems are also challenging as follows: (1) *Cyberattacks*: In the event of mainstream usage, Cyberattacks will compromise students' data storage. Indeed, data security should be a strength of data servers such that users feel secure that no unauthorized access will occur (Kasneci et al., 2023). (2) *Authentication*: If adopted, ChatGPT may have to establish a suitable screening mechanism for personal and institutional authentication of user data including necessary filters and camouflage. This would invite substantial investments in infrastructure and technical know-how (Agapito, 2023), which might be in its nascence owing to the sophistication of these language-enabled models and systems. (3) *Compliance*: A revamp of regulations that comply with currently existing data security standards and regulations associated with the adoption of ChatGPT in educational settings may be complex and time-consuming (Stahl, 2021; Kasneci et al., 2023). For example, the General Data Protection Regulation (GDPR) mandates that user institutions should execute suitable technical and institutional measures to protect user data (Geko and Tjoa, 2018). (4) *Data storage*: The processing of generative models will mandate storage of large amounts of user data. This makes all data vulnerable to data breaches and other security infringements (Deng and Lin, 2023), requiring significant investment in secure storage machinery, continuous data development, security retention, and deletion policies (Kasneci et al., 2023).

4.5. Ethical challenges

4.5.1. Partiality in training data

Scholars note the significant amount of partiality in the input-training data to train the model (Akter et al., 2021; Böhm et al., 2022; Dwivedi et al., 2023a) as follows: (1) *Reinforcing stereotypes*: In cases where the input data is biased or based on prejudicial language, this situation will influence the quality of responses such that output that is compromised will not meet students learning needs (Bender et al., 2021; Getahun, 2023). Recent studies found that queries related to mental patients were highly biased around stereotypes thus compromising data quality (Chin et al., 2023; Potts et al., 2021). This raises an important question on the suitability of ChatGPT for learning systems where training data quality is critical to the usability of the system for a particular purpose (Hamilton, 2022; Heikkilä, 2023). (2) *Absence of diversity in data*: One complex challenge concern input-trained data generating like-natured outputs (Weissglass, 2022). For example, a ChatGPT model trained on data customized for a certain set of audiences may fail to furnish precise or comprehensive answers to learners outside of the discipline or specialization (Bjork, 2023). Thus, partial or inappropriate data is being rendered to learners bringing to the forefront many existing disparities in the whole education system (Chen et al., 2023). This portrays the need for preparing and fine-tuning the input content (training) data for downstream errands. Scholars suggest that generative models specific to disciplines have to be dissimilar, distinct, and representative to that specific group of learners or individuals (Kasneci et al., 2023). However, this strategy may make the data unusable for other more general users (Yang, 2022; Hartmann et al., 2023). Timely and frequent scrutiny and analysis of the application's suitability and functioning on distinct profiles and assemblies of users can help to diagnose and eradicate gaps and embedded predispositions (Stahl, 2021). The human component of the whole system is integral requiring greater need for monitoring, determining the input quality and accounting for bias (Krügel et al., 2023).

Our discussions thus far suggest that many adoption challenges exist related to the adoption of AI technology in general and ChaptGPT in particular. For instance, while human input is critical for creative, intelligent and high-quality contextual output, administrators and designers need to place problems of data privacy and confidentiality at the forefront of potential solutions. Consequently, it will be necessary to develop a range of strategies and solutions that at least in part help to address many of these AI adoption problems and challenges discussed earlier. In respect of the current paper and based on emerging research illustrated in Table 2 earlier, we next outline what these strategies might look like in respect of the education sector.

5. Strategies to support the education sector in using ChatGPT

5.1. Strategies related to inadequate human interaction.

Strategies to address the challenges of poor human interaction in the institutionalization of ChatGPT should be considered within the context of other teaching aids, tools and educational strategies. ChatGPT should be considered as a complementary aid and not as a substitution for poor human interaction which we discuss next (Gong et al., 2018; Gao, 2021; Jalil et al., 2023; Dwivedi et al., 2023a). That is, based on the emerging themes in Table 2 and subsequent discussion, it is possible to develop what some of these strategies might look like based on the emerging challenges identified thus far.

- *Blended learning*: The latter is a format of education consisting of online learning blended with face-to-face instruction. By combining ChatGPT with other teaching methods such as in-person lectures, group discussions, and collaborative learning activities, educators can help ensure that students have opportunities to interact with their peers and instructors in a more social and engaging learning environment (Gong et al., 2018). Here, ChatGPT should act as a support function to the person-driven education system.
- *Personalized learning*: Personalized learning bespoke instructional method caters to individual student needs and learning styles (Dwivedi et al., 2023a). By using ChatGPT as a means to provide pupils individualized-specific feedback, guidance, and support, educators can help to create a more individual-adaptive and engaging process that is tailored to the needs of each student.
- *Collaborative learning*: This format is a sought-after educational aid which emphasizes group work and teamwork. ChatGPT could be a very innovative tool to help facilitate group discussions, peer feedback, and collaborative learning activities, which educators could harness to offer opportunities of interaction, engagement and collaborative learning with fellow-learners and peers (Jalil et al., 2023). In fact, collaborative forms of learning might increase social and teamwork skills because of the opportunity for teamwork.
- *Use of ChatGPT as a learning tool*: Teachers can materialize this application/platform to complement traditional teaching methodologies rather than as a replacement for them (Dwivedi et al., 2023a). By using ChatGPT to afford learners additional resources and feedback, with careful supervision, educators can help to create a collaborative, interactive, customized and engaging learning experience while building reflective human interaction as a consequence of using the model.

5.2. Strategies related to limited understanding.

Some strategies that can help to overcome limited understanding of ChatGPT in the education sector include the following:

- *Pre-training on educational data*: To improve the accuracy of ChatGPT in the educational domain, pre-training on educational data can be implemented with timely updates and maintenance. This approach mandates training of the model on large and diverse datasets of educational texts not restricted to textbooks, lectures, and educational videos (Sallam, 2023). Such modification strategies should help the model to assimilate, encrypt, better understand and generate responses to educational queries which will enhance the quality of output responses.

- *Use of knowledge graphs*: Knowledge graphs can be used to represent and store knowledge about a particular domain within the education sector (Chicaiza and Valdiviezo-Diaz, 2021; Kasneci et al., 2023). Knowledge graphs can be beneficial to improve application understanding by providing ChatGPT with additional knowledge about a topic within a context. This can advance the accuracy of the responses generated by ChatGPT by empowering the tool to better decrypt, understand and react to inquiries related to the education domain.
- *Fine-tuning on specific tasks*: Fine-tuning ChatGPT on specific tasks or topics can help improve its understanding and accuracy in these areas (Kasneci et al., 2023). For example, by fine-tuning the model on specific educational tasks such as answering questions about a particular topic or providing feedback on student writing, ChatGPT can be trained to generate more accurate and relevant responses.
- *Human-in-the-loop approach*: The human-in-the-loop approach involves incorporating human intelligence input into the model training process (Wu et al., 2022). This approach can be used to help advance the understanding of ChatGPT by allowing humans to correct errors and provide feedback to the model by increasing the precision and relevance of the model's output-responses.

5.3. Strategies related to absence of creativity

Strategies that can help minimize the absence of creative input in generative models include the following:

- *Incorporating creative prompts*: One strategy to promote creativity in ChatGPT responses is to incorporate creative prompts into the training data (Kasneci et al., 2023). Creative prompts will comprise a component/criterion set of iterations where users can have the liberty of choosing the output that suits his or her specific need. One downside is that this can only be relevant to mature users of pedagogy and education.
- *Training on diverse genres*: Training ChatGPT on a diverse range of genres can help promote creativity in the model's responses (Haleem et al., 2022). By incorporating diverse genres, ChatGPT can learn to generate responses that are more imaginative and creative. Moreover, a criterion of naivety scale could be introduced which would help users to modulate between the complexities of content derived from the application.
- *Incorporating human input*: Incorporating human input into the training process can help promote creativity in ChatGPT responses as noted earlier (Cooper, 2023). By allowing humans to review and provide feedback on the model's responses, ChatGPT can learn to generate more creative and imaginative responses.

5.4. Strategies related to dependency on data

Strategies that can help to avoid the dependency on data of ChatGPT in the education sector include the following:

- *Incorporating domain-specific knowledge*: Incorporating domain-specific knowledge in the input/training data can help to reduce the reliance on general training data (Zhu et al., 2023). By providing domain-specific knowledge, ChatGPT can be programmed to cater to relevant and authentic data pertaining to a specific need.
- *Transfer learning*: Transfer learning enables the application model to learn from pre-trained models thus reducing the dependency on general data knowledge (Kasneci et al., 2023), which might also reduce the magnitude of training data and operational effort.
- *Active learning*: Active learning is a technique that can decrease the breadth and volume of data required for model training (Budd et al., 2021). In this format, the model is iteratively trained on small chunks of data which is improvised and added iteratively such that performance and quality output is improved.
- *Data augmentation*: This technique can help to increase the amount of data available for training which can reduce the dependency on data (Maharana et al., 2022). Data augmentation involves spawning new data from currently existing data by adding or making small modifications. Though this technique could be exposed to allegations of salami slicing, measures can be taken to impair its resemblance and fundamental nature.

5.5. Strategies related to training and maintenance expenditures

Overcoming the costs of training and maintenance expenditures should include the following:

- *Leveraging open-source resources*: Open-source resources can help reduce the cost of training and maintenance (Kasneci et al., 2023). By using open-source ChatGPT models and code, educational institutions can avoid the cost of developing a custom solution from scratch.
- *Using pre-trained models*: Pre-trained models can reduce the amount of training required for a specific task (Han et al., 2021). These models are trained on large datasets and can be tailored to specific specialized tasks reducing the amount of training required. Timely updates would also be required on pre-trained models.
- *Using cloud-based services*: Cloud-based services can help to reduce the cost of maintenance by outsourcing the management of the infrastructure to a third-party provider (Ali et al., 2022). This approach can also reduce the need for in-house IT staff resulting in reduced costs.
- *Prioritizing maintenance*: Prioritizing maintenance is critical to avoid long-term costs (Kasneci et al., 2023). Regular maintenance can help to identify and fix problems before they become overly expensive. Prioritizing maintenance is also integral to stamping out plagiarism and to ensure secure user identity and data security.

5.6. Strategies related to inadequate contextual understanding

The ability of generative models to facilitate greater contextual understanding should include the following:

- *Multi-task learning*: This technique empowers designers to improve the model's understanding of the context. In this format, the model is trained to juggle and deliver between multiple parallel tasks which can help it to learn more about the context (Kasneci et al., 2023). Multi-task learning should significantly eradicate problems associated with contextual irrelevance of ChatGPT in the education sector. In negotiation a way forward at least within a non-technical process, designers could work with educational providers to create different user or learner contexts that a string of code might apply too. For instance, if a user types in 'team learning', the application will search training data for all it knows about team learning. However, if team learning is advanced to multiple contexts with different interpretations and then embedded in training data, output quality related to multi-tasking should improve.
- *Pre-processing the data*: Pre-processing the data can help to provide the model with additional contextual information (Dwivedi et al., 2023a). This can include adding metadata to the data, such as author or publication date, or using techniques such as named entity recognition to identify important entities in the text.

- *Interactive learning*: Interactive learning involves allowing users to provide feedback to the model in real-time, which can help it to improve its understanding of the context.

5.7. Strategies related to the limited ability to personalize instruction

Currently, the inability of ChatGPT to personalize instruction can be addressed in the following ways:

- *Using student-specific data*: One way to improve the ability to personalize instruction is to use student-specific data such as previous student records of performance, individual interests, and learning style (Kasneci et al., 2023). This data can be used to customize the teaching method to specific individual needs and account for informed consent from either the student or their guardians.
- *Implementing adaptive learning systems*: This system uses machine learning algorithms to probe student data and fine-tune instruction to individual needs in real-time (Zhou et al., 2021). The inclusion of tutors in this process could be one technique that can be considered while preparing the system for user-specific functions.
- *Using natural language processing* (*NLP*): These techniques are materialized to analyze student writing and provide feedback that is tailored to their individual needs (Bernius et al., 2022). For example, NLP can be used to identify areas where learners require iterative practice and instructional material and require targeted exercises to improve user skills.
- *Incorporating human instructors*: While ChatGPT can be useful for providing personalized instruction, it is important to also incorporate human instructors into the learning process (Kasneci et al., 2023). Human instructors can offer greater guidance, support, and advice that is bespoke and personalized to each student's needs.

5.8. Strategies related to sustainable usage

Strategies that will help to achieve sustainable usage of ChatGPT in the education sector include the following:

- *Prioritizing energy efficiency*: Using energy-efficient hardware and software can help to reduce the environmental impact of using ChatGPT (Qadir, 2023). This would need the indulgence of complementary sectors to gain new knowledge of research and practice ensuring that hardware addresses the sustainability of the ecosystem.
- *Developing ethical guidelines*: Developing ethical guidelines for the specific use of ChatGPT in the education sector will help in its sustainable use over time and that it will not be harmful socially and environmentally (Mhlanga, 2023). The collaborative efforts of all stakeholders such as regulatory bodies and policy-makers should be considered in relation to formulating these ethical guidelines.
- *Encouraging responsible use*: Encouraging responsible use of ChatGPT among students and staff can help to minimize the impact of its use on the environment (Michel-Villarreal et al., 2023). Teachers can be an integral part of this process to ensure responsible use of technology occurs.
- *Promoting alternative solutions*: Alternative education solutions and pedagogical practices continue to exist (Dwivedi et al., 2023a). Students should be empowered to make complementary use of generative models however as the AI features of these programs continue to improve.

5.9. Strategies related to data security and privacy

Strategic solutions related to data security and privacy issues can be addressed as follows:

- *Implementing strong authentication and access controls*: Implementing robust authentication and access restrictions is one technique to protect data security and privacy (Gupta et al., 2023). This involves employing multi-factor authentication, role-based access management, and strong password criteria to provide authorized access to student data.
- *Regularly updating security systems*: Security systems must be regularly updated to prevent cyberattacks (Gupta et al., 2023). This includes applying software patches and using up-to-date antivirus and malware detection software.
- *Monitoring and logging*: Monitoring and logging are important strategies for identifying security breaches and preventing unauthorized access to student data (Dwivedi et al., 2023a). These logs can also help to identify any data privacy violations and allow for quick remediation.
- *Educating staff and students*: Educating staff and students about data security and privacy is essential for creating a culture of cybersecurity (Alshaikh, 2020). This includes teaching users about password management, phishing problems, and other types of cyberattacks.
- *Conducting regular risk assessments*: Timely and routine risk valuations (Kasneci et al., 2023) can support the identification of vulnerabilities in the system and ensure that appropriate measures are taken to prevent data breaches and cyberattacks.

5.10. Strategies related to bias in training data

Our research suggests that the pre-existing biasing of data can be addressed as follows:

- *Diverse data collection*: Diverse data collection involves collecting data from a range of sources and perspectives to garner that input training data is illustrative and atypical of the population (Bogina et al., 2022), which should also be frequently updated to accommodate user needs.
- *Human-in-the-loop approach*: A human-in-the-loop approach can also be used to help eliminate biasing of the data (Wu et al., 2022). By allowing humans to review and provide feedback on the training data, biases can be identified and corrected leading to more accurate and inclusive responses.
- *Regular data audits*: Regular data audits involve reviewing the training data on a timely basis to eradicate bias and prejudice that could have been introduced over time (Ayinde et al., 2023). By reviewing the data regularly, generative models will be able to continuously generate accurate and quality outputs.

Taken together, the earlier classification framework list in Table 2 has enabled the researchers to identify how the gaps and challenges of generative AI models such as ChatGPT can be addressed by their matching strategies. While the strategies outlined are specifically related to the education sector, they might also be generalized as potential solutions for the challenges faced by other sectors e.g., the manufacturing sector, given that common concerns such as data security, contextual understanding, and personalized instruction for example may be common across institutions and industry settings. Although the current review has been based on the compilation of current and extant research, our findings represent potential pathways by which future research endeavors can be explored. The authors hope however that this review might move extant research forward by helping to mitigate against the significant challenges posed by generative AI models. We now turn to a discussion of what these future directions look like.

6. Conclusion

The novelty of ChatGPT as a generative model of AI for intellectual output creation has been one of the most significant innovations of contemporary times. However, this review responded to calls for a more well-researched literature on the theme. Given that machine learning has enabled hi-tech content generation and innovation pertaining to digital content initiation, this process has naturally progressed to sophisticated AI technology as a constant theme for most digitally-dependent fields of inquiry. We explored in the current study for instance how AI generative models create artificial relics by scanning through the input training specimens that are used to train input data. We also outlined how these features are explored through ChatGPT as an example of a generative model leading to the development of a comprehensive classification framework which was outlined in Table 2. We next identified the strategies that can be implemented as solutions to the challenges presented. We noted for instance that ChatGPT has the potential to transform the educational sector through digital means and we analyzed what this process might look like on the basis of the challenges presented.

6.1. Limitation, and future research directions

Several limitations can be observed for the current review. First, the manuscript and search process categorically focused on published articles in peer-reviewed journals and reputable databases. Thus, we have not looked at books and book chapters and have used a limited longitudinal design over a designated time period. This process may have eliminated other seminal and related digital and technology related literatures. Second, our methodology could be sequenced for future investigations by including a broader number of keywords, data repositories, and unreported/unpublished data. Use of such literature should be cautiously undertaken by applying specific quality parameters. This review is also limited by the emerging themes presented and the authors' interpretation of these. For instance, other authors might have different interpretations of data nuances to the extent that they search for a different range of articles. This would also be similar for other emerging themes. Moreover, the authors have taken a broad-church approach to review the available literature by focusing on the findings of studies related to broader educational fields. Thus, our review findings are limited by generalizing the findings to more general features of a specific educational effect such as learner experiences, the use of personalized human tutors. Accordingly, these limitations may result in future opportunities for scholars in subsequent research by focusing on the specific effects of generative AI models within a unique educational institution such as schools, as well as a more micro-focused methodology on particular features of the application.

Extant studies including the current research suggests that ChatGPT is becoming pivotal in all walks of life inter alia education and many more. The current study indicates an emerging requirement for a detailed study on ChatGPT and what this might look like for different technological advances in to the near future. Moreover, consistent research endeavors are required to substantiate the field of research and practice. The current review can aid in the development of a unified theoretical framework to act as a reference point to future ontological fields of inquiry and focused investigations. To this end, the authors hope that the gaps and challenges identified might motivate other scholars to empirically test all or parts of the framework for future research. Future research for instance might explore the effects of generative models on other theoretical designs such as information systems, organizational learning, and in health-related areas such as electronic health records. Scholars might explore the convergence of different theories of innovation such as the theoretical Acceptance Model (TAM) and the Transfer of Technology (TOT) model for example by exploring how these mid-range theories influence the technical, operational and organizational nuances of AI-enabled models. The future generation of researchers might investigate the promising dimensions of ChatGPT. While this area of investigation is still in its nascence, its holistic adoption in varied sectors has been swift and integral. While generative AI has experienced a slower uptake in the education sector, there is little doubt that AI technology could revolutionize the way education is offered, dispensed, aggregated and assimilated.

CRediT authorship contribution statement

Omar Ali: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Peter A. Murray:** Conceptualization, Investigation, Resources, Supervision, Writing – review & editing. **Mujtaba Momin:** Conceptualization, Resources, Writing – review & editing. **Yogesh K. Dwivedi:** Conceptualization, Supervision, Writing – original draft, Writing – review & editing. **Tegwen Malik:** Writing – review & editing.

Declaration of competing interest

There are no conflicts of interest for this manuscript.

Data availability

No data was used for the research described in the article.

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Omar Ali is an Assistant Professor in information systems at Abdullah Al Salem University, Kuwait, where he currently teaches business process and systems, and operations management. He received his PhD in Management Information System (MIS) from University of Southern Queensland (USQ), Australia. Also, he had two master degree. The first one in Information and Communication Technology, and the second one in Information Systems and Technology by research, both of the master degree from University of Wollongong. His

research interests include RFID; cloud computing; blockchain; artificial intelligent; security; and system analysis and design. He is reviewer for many leading journals such as government information quarterly, information systems management, and behaviour and information technology. Also, he has published in top international leading journals such as international journal of information management, technological forecasting and social changes, journal of innovation and knowledge, government information quarterly, information technology and people, and behaviour and information technology.

Peter A. Murray works in the School of Management and Enterprise at the University of Southern Queensland. His research interests focus on two main themes: 1) high performance work & leadership studies and 2) organizational transformation & diversity. Peter does applied research in employee engagement and team learning in local government settings which follows much of his earlier research in organizational learning in large public and private corporations. He is also a regular reviewer for many leading journals and his published work appears in high ranked journal outlets such as Supply Chain Management, Human Resource Management Journal, Asia Pacific Journal of Human Resources, International Journal of Human Resource Management, Management Learning and many others. Peter has a strong history of organizational development consultancies and training to very large corporate organizations throughout Australia.

Mujtaba Momin is an Assistant Professor in Human Resource Management (HRM) at the American University of Middle-East, Kuwait (In Affiliation with Purdue University Indiana USA). He has previously worked with Prince Salman Bin Abdul-Aziz University, Kingdom of Saudi Arabia. In addition to broader areas of interdisciplinary relevance, his research interests include technology and HRM, employability skills enhancement; entrepreneurship; CSR, developing industry-academia interface; interpersonal and communications skills enhancement.

Yogesh K Dwivedi is a Professor of Digital Marketing and Innovation and Founding Director of the Digital Futures for Sustainable Business & Society Research Group at the School of Management, Swansea University, Wales, UK. In addition, he holds a Distinguished Research Professorship at the Symbiosis International (Deemed University), Pune, India. Professor Dwivedi is also currently leading the *International Journal of Information Management* as its Editor-in-Chief. His research interests are at the interface of Information Systems (IS) and Marketing, focusing on issues related to consumer adoption and diffusion of emerging digital innovations, digital government, and digital and social media marketing particularly in the context of emerging markets. Professor Dwivedi has published more than 500 articles in a range of leading academic journals and conferences that are widely cited (more than 65 thousand times as per Google Scholar). He has been named on the annual Highly Cited Researchers™ 2020, 2021 and 2022 lists from Clarivate Analytics. Professor Dwivedi is an Associate Editor of the *Journal of Business Research*, *European Journal of Marketing*, and *Government Information Quarterly*, and Senior Editor of the *Journal of Electronic Commerce Research*.

Tegwen Malik has an applied project management and multi-disciplinary background. Her focus for many years has been in research and innovation for both the sciences and management areas with a particular interest in international standards, sustainability and bio-inspiration. In her work she regularly turns to nature's evolutionary solutions to harness and inspire greener and more sustainable solutions and innovations.