Image and Vision Computing 154 (2025) 105347

Contents lists available at ScienceDirect

Image and Vision Computing

journal homepage: www.elsevier.com/locate/imavis

Generative AI in the context of assistive technologies: Trends, limitations and future directions

Biying Fu [a,b,*], Abdenour Hadid [c], Naser Damer [b,d]

[a] RheinMain University of Applied Sciences, Wiesbaden, 65195, Hessen, Germany
[b] Fraunhofer Institute for Computer Graphics Research, Darmstadt, 64283, Germany
[c] Sorbonne Center for Artificial Intelligence, Sorbonne University Abu Dhabi, Abu Dhabi, United Arab Emirates
[d] Department of Computer Science, TU Darmstadt, Darmstadt, 64283, Hessen, Germany

ARTICLE INFO

Keywords:
Assistive AI
Generative AI
Generative models
Assistive systems
Assistive technologies and services

ABSTRACT

With the tremendous successes of Large Language Models (LLMs) like ChatGPT for text generation and Dall-E for high-quality image generation, generative Artificial Intelligence (AI) models have shown a hype in our society. Generative AI seamlessly delved into different aspects of society ranging from economy, education, legislation, computer science, finance, and even healthcare. This article provides a comprehensive survey on the increased and promising use of generative AI in assistive technologies benefiting different parties, ranging from the assistive system developers, medical practitioners, care workforce, to the people who need the care and the comfort. Ethical concerns, biases, lack of transparency, insufficient explainability, and limited trustworthiness are major challenges when using generative AI in assistive technologies, particularly in systems that impact people directly. Key future research directions to address these issues include creating standardized rules, establishing commonly accepted evaluation metrics and benchmarks for explainability and reasoning processes, and making further advancements in understanding and reducing bias and its potential harms. Beyond showing the current trends of applying generative AI in the scope of assistive technologies in four identified key domains, which include care sectors, medical sectors, helping people in need, and co-working, the survey also discusses the current limitations and provides promising future research directions to foster better integration of generative AI in assistive technologies.

1. Introduction

Generative artificial intelligence (AI) models have recently gained significant attention and excitement in society. The remarkable success of large language models like ChatGPT [1] for text creation, along with image generation transformer models such as Dall-E [2], Stable Diffusion [3], and Midjourney [4], has demonstrated the potential of these technologies to seamlessly integrate into various aspects of daily life [5]. These advancements have had a profound impact on diverse fields, including the economy [6], education [7,8], entertainment [9, 10] such as the gaming and multimedia industry, E-Commerce [11] for making personalized recommendations, law and legislation [12], computer vision [13,14], and finance [15].

The rise of generative AI in healthcare has been triggered in recent years with the introduction of advanced learning algorithms, enhanced computing infrastructures, and the availability of larger amounts of data. Generative AI has found its way into molecular biology [16], medical education [17], clinical decision support [18], and the development of novel drug discoveries [19]. The technology successfully showcased its efficiency in finding the optimum structures for new medicines through large quantities of existing data or helping the clinicians in their decision-making process by providing diagnostic assistance in the forms of a list of possible diagnoses and treatment plans.

In this work, we mainly focus on the use of generative AI in the realm of assistive systems. The term "assistive systems" is not limited to assistive tools designed specifically for people with disabilities, but encompasses a much broader spectrum that can extend to large systems, services, processes, frameworks, and even infrastructures [20]. These systems could benefit not only individuals but also organizations and infrastructures. Assistive technologies are relevant in all areas of life, ranging from private homes, medical sectors, and care sectors to the professional world. For enhancing the quality of generative AI involvement in such systems, the dialog between the developer, care workforce, and the people who receive the care is important to improve the status quo [21]. Thus generative AI greatly enhances the efficiency of healthcare by automating and simplifying tasks or

* Corresponding author at: RheinMain University of Applied Sciences, Wiesbaden, 65195, Hessen, Germany.
E-mail address: biying.fu@hs-rm.de (B. Fu).

https://doi.org/10.1016/j.imavis.2024.105347
Received 15 August 2024; Received in revised form 14 October 2024; Accepted 25 November 2024
Available online 30 November 2024

processes traditionally performed by humans, but with higher speed and reduced costs, thereby benefiting patients, doctors, hospital administrators, and thus communities. In the healthcare sectors, generative AI manifests in various successful applications, e.g., in supporting research in drug discovery [22], in the teleoperation of robots that assist in surgeries [23,24], the automation of administrative functions or processes [25] in a clinical context, the provision of personalized cares [25], and much more. In this comprehensive survey, we aim to delve deeper into the different perspectives of using generative AI in assistive systems and show both opportunities and limitations. We want also to raise awareness of potential risks while benefiting from the comfort of generative AI in assistive systems. Compared to existing surveys in the literature, we are the first targeting the research of generative AI in the context of assistive technologies in such depth and broad scope. Previous surveys predominantly focused on certain aspects of generative models, such as the general use of large language models [26], the fairness issue in LLMs [27], the hallucination problem [28], and the explainability issues [29] or its use in a limited domain, such as only healthcare [30,31]. None of these surveys are focused on collecting the use-cases of generative AI in the specific domain of assistive technologies in a much broader sense, showing trends, limitations, and future directions.

The rest of this article is organized as follows: Section 2 introduces the concept of generative AI, followed by a clear definition of assistive systems in Section 3. In Section 4, we conduct an extensive literature review to identify potential interactions, current trends, and promising use-cases for leveraging generative AI for assistive systems. Section 5 summarizes popular technical stacks of generative AI methods used in the domain of assistive systems. In Section 6, we discuss the limitations of generative AI for assistive systems. Then, we present possible research directions to address the challenges in Section 7. Finally, we conclude our work in Section 8.

2. The emergence of generative AI

In this section, we provide a brief overview of the history of generative models. We will discuss these foundational approaches before exploring the more recent generative AI technologies that have been developed specifically for assistive systems, which will be covered in detail later. We also review studies and successful examples showing how these applications are prioritized in the domain of assistive technologies.

2.1. Types of generative models

Generative models have a long history. Generative models are a class of machine learning algorithms designed to generate new data samples that resemble a given training dataset. By learning the underlying distribution of the training data, generative models can produce novel outputs that are not pure replications but rather new instances that share similar characteristics.

Its development begins with early probabilistic models like Gaussian Mixture Models (GMMs) [32] and Hidden Markov Models (HMMs) [33] that were well suited for modeling sequence data and laid the groundwork for understanding data distributions. In the 2000s, advances in deep learning led to the introduction of more sophisticated generative models, such as the *Variational Autoencoder* (VAE) [34] and *Generative Adversarial Networks* (GANs) [35], which revolutionized the field by enabling the generation of highly realistic images, text, and audio. More recently, *diffusion models* [36] further improved the ability to generate high-quality and diverse outputs across various types of data. Lately, the *large language models* (LLMs) have further pushed the boundaries of generative AI, particularly in natural language processing (NLP) and multimodal tasks for assisting humans in various tasks.

Variational Autoencoder: Introduced by Kingma et al. [34] in 2013, VAE is a type of generative models that combines principles from both neural networks and statistical inference [37] to generate new data similar to its training data. VAEs consist of an encoder and a decoder structure and are mainly used to learn meaningful representations of input data in a latent space [38] and the data manipulation can be performed directly on this latent space [39]. After the successful training of a VAE model, the decoder part of the network can be used to generate new data that strongly resembles the original inputs [40]. The VAE training is more stable and provides a more interpretable latent space compared to GANs by only combining two different losses in the overall loss function, which are the reconstruction loss and the Kullback–Leibler Divergence loss [41]. VAEs have found applications in various fields, including image generation [42], anomaly detection [43], representation learning, and attribution learning [44].

Generative Adversarial Networks: They are a class of machine learning frameworks first introduced by Ian Goodfellow et al. [35] in 2014. GANs consist of two neural networks, the generator and the discriminator, which are trained simultaneously through an adversarial process. This is a two-party play engaged in a zero-sum game under a game theoretical perspective. While the generator is trained to produce synthetic data from random noise that resembles high-quality real data, the discriminator network aims to differentiate between these generated fakes and actual real data. GANs are notably difficult to train due to a problem called mode collapse [35], which means that the generator outputs are limited in the variety by effectively ignoring some regions of the data distribution. Other challenges in training GAN architectures are the unstable training dynamics, sensitive hyperparameter tuning, gradient saturation, and the balancing of the generator and discriminator training [45]. GANs have successfully found applications in medical domains, such as in image synthesis for generating magnet resonance imaging [46], data augmentation for improving skin-lesion analysis [47], and style transfer to overcome the limitation of data unavailability as in [48]. Other applications can be found in biometrics e.g. synthesizing realistic face images of specific identities to be used in the training or evaluation of biometric systems [14,49–51].

Diffusion models: These concepts in the context of generative modeling originate from statistical physics and stochastic processes, particularly the study of thermodynamics and the behavior of particles. One of the pioneering works in applying diffusion processes to generative modeling was by Sohl-Dickstein et al. [52] in 2015. A significant advancement came with the introduction of Denoising Diffusion Probabilistic Models (DDPMs) by Ho et al. [36] in 2020. Diffusion models using diffusion process consist of two sequential processes which include first the forward process and followed by a reverse process. In the forward process, noise is gradually added to the data transforming it into a simple distribution such as the Gaussian noise. In the reverse process, the model learns to remove the noise step-by-step, reconstructing the original data from the noisy distribution. To generate new data after training, the model starts with a sample from the simple noise distribution (e.g., Gaussian noise) and iteratively applies the learned denoising steps to transform it back into a noise-free high-quality sample mimicking the sampling from the original data distribution. The proposed DDPMs further refined the reverse diffusion process using a neural network, achieving state-of-the-art performance in image generation tasks. Diffusion models have demonstrated their ability to generate samples with high fidelity and diversity, comparable to or surpassing GANs, while at the same time enabling stable training. Recent applications showed diffusion models in various tasks such as in image synthesis [53], synthesizing realistic face images for different purposes [54,55], inpainting [56], and super-resolution [57].

Large Language Models: These models and generative AI are closely related concepts in the field of AI, with LLMs often being a specific type of generative AI focused on NLP. LLMs are a class of AI models built using advanced deep learning techniques, particularly based on transformer architectures [58]. LLMs, such as GPT-3 by OpenAI [1], BERT by Google [59], Llama by Meta [60] and others, are designed to understand and generate human language. Trained on vast amounts of human text and languages, they learned the complexities of language, grammar, context, and even nuances of meaning. Thus, these models are able to generate human-like and human-understandable text. LLMs are a specific type of generative AI focused on text. Recently, multimodal LLMs [61] represent an emerging area of research, which take into account different input modalities to enhance the understanding and generation capabilities of traditional text input LLMs. These models prioritize refining the alignment between various modalities and aligning them with human intent, thus enabling improved content comprehension and text generation. Notable projects like BLIP-2 [62] and LLaVA [63], which combine textual and image inputs, have demonstrated significant improvements in accuracy for tasks such as visual question answering. They find applications across various sectors, including education, healthcare, customer service, entertainment, and research.

2.2. How these applications are prioritized?

VAEs, GANs, and diffusion models are mainly used for data generation. Several studies show how these applications are prioritized in the domain of medical imaging. Islam et al. [64] and Kazeminia et al. [65] reviewed the use of GANs for medical image generation and analysis. The results have demonstrated that GANs can be leveraged not only for data augmentation [66] but also to enhance classification [67] and segmentation [68] accuracy in medical sectors. In [66], Chen et al. reviewed 105 research papers on the use of these generative models related to medical image augmentation, sourced primarily from ELSEVIER, IEEE Xplore, and Springer between 2018 and 2021. The authors categorized these papers based on the specific organs represented in the medical images. The sheer number of relevant use-cases illustrates the priority of such models in the field of medical imaging.

Powerful LLMs can be leveraged to extract specialized contexts, particularly in assistive technologies, where they can enhance user interaction [69] and provide personalized support [70] according to current reviews. Some successful applications include generating real-time communication assistance for individuals with speech impairments [71], offering tailored learning experiences for students with special needs [72], and aiding in cognitive rehabilitation by generating adaptive exercises [73]. These models can also be integrated into smart devices [74,75] to assist elderly or disabled individuals in navigating daily tasks, thus fostering greater independence and improving overall quality of life. In addition, the works of [76,77] investigated the possibility of using multimodal LLM with visual instruction to guide visually impaired people to navigate through their surroundings.

3. The world of assistive technologies

Assistive systems refer to a broad category of technologies designed to support individuals in performing tasks they might otherwise find challenging due to physical, sensory, cognitive, or emotional impairments. These systems aim to enhance the quality of life, increase independence, and provide support in daily activities.

An assistive technology device is defined by the Tech Act in 1988 [78] as "any item, piece of equipment, or product system, whether acquired commercially, modified, or customized, that is used to increase, maintain, or improve functional capabilities of individuals with disabilities". This accounts not only for devices but also for services and technologies. Assistive systems already found applications in various domains, such as in production environment [79], for the workplace [80], and in care facilities [81].

A common misconception is that assistive systems are exclusively needed by the elderly; however, individuals of all ages, including younger people and adults, can also benefit from these systems. Beyond the use for people with impairments, these assistive technologies are even for people without disabilities but incline to increase their comfort. In the following, we are looking at uses-cases of assistive systems enhanced with generative AI approaches in various areas. We investigated several application domains using generative AI for assistive systems in this comprehensive survey and identified four key domains, which we think are most influential and promising. In Fig. 1, we visualized the overview of the targeted domains using assistive technologies with generative AI. They encompass the use-cases of generative AI in the care sectors, medical domain, helping people with need, and as a virtual co-creation or co-working partner.

4. On the use of generative AI in assistive systems

In this section, we examine the possible interactions between generative AI solutions as part of the building process of assistive systems or technologies. Thereby, we consider the four identified main areas of use as illustrated in Fig. 1, ranging from the use-cases in the care sectors, in the medical sectors, for helping people with disability, and last but not least for supporting people looking for general assistance and more comfort.

4.1. Generative AI applications in the care sectors

The adoption of innovative solutions within healthcare has predominantly been examined from the standpoint of patients, although such a perspective is acknowledged to be limited and narrow [82]. Thus, Nugent et al. [21] extended their investigation to include the perspectives of caregivers, healthcare professionals, and, on a broader scale, healthcare service providers. In their study [21], the authors formulated a prototype framework to efficiently evaluate the adoption of innovative healthcare solutions, employing generative AI. Generative AI is employed herein to facilitate the generation of a set of patient-centered questionnaires, aiding researchers and caregivers in navigating the process of technology adoption within healthcare contexts. The aim is to identify the true requirements and provide proper care.

Revell et al. [83] examined the necessity of integrating generative AI applications within the healthcare and well-being sectors. The increasing demand for AI services arises from the progression of population aging and the accompanying shortage of skilled workers, which poses a significant challenge. The authors underscored the need for socially assistive robots, while at the same time highlighting criticisms regarding existing systems, including biases, lack of transparency, and privacy concerns. Current interactions with these robots are constrained to brief engagements, presenting notable hurdles for achieving broader user acceptance. Moreover, they emphasized the importance of having training databases without situational, cultural, gender, and racial biases. As a proposed solution, the authors advocate for the development of virtual/robotic assistive systems that require niche language models instead of general language models.

For improving the quality of care-giving by assistive robotics, current trends take advantage greatly from the advancements in AI and generative AI. This is especially beneficial for the increasing demands of individuals requiring assistance in our society e.g. due to aging, people with physical disabilities, or war-related injuries. A report from the World Health Organization recently stated [84] that over 2.5 billion people worldwide currently require one or more assistive products. With the issue of global population aging, it is projected that by 2050, around 3.5 billion people will need access to assistive technologies. Tytarenko et al. [85] studied the possibility of applying diffusion model concepts as a policy learning strategy in the reinforcement learning paradigm to train assistive robots that can better and individually serve the needs of humans. The suggested approach harnesses the advantages of both model-free reinforcement learning and imitation learning techniques. By further utilizing diffusion models to enhance the robustness of policy making strategy they achieved a more independent agent without requiring further interactions with the environment.

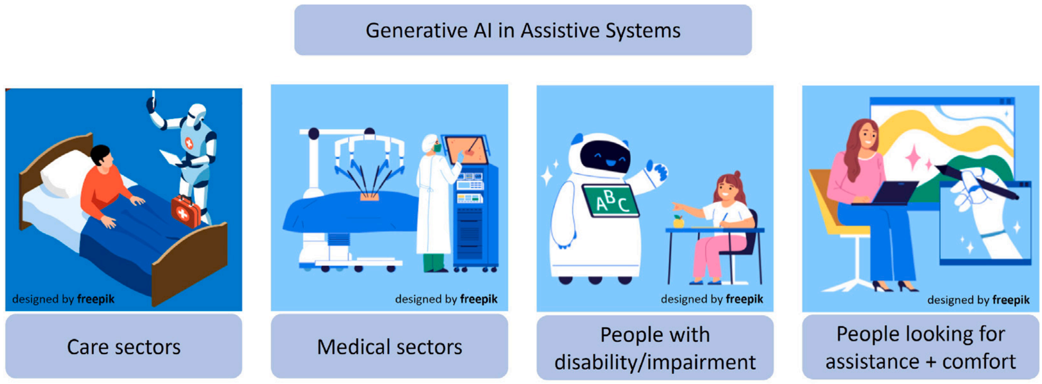

Fig. 1. visualizing the four main sectors in this article, we considered most influential and promising, where the generative AI technology is used in building the assistive systems.

Adedeji et al. explored in [86] the potential of reducing the documentation workload for medical and healthcare staff by enhancing the accuracy of automatic speech transcription (AST) using LLMs. The authors demonstrate that LLMs, supported by Chain of Thought prompting, can significantly improve the record-keeping accuracy of existing AST systems, achieving performance competitive with state-of-the-art systems in this domain. This improvement includes accurate capturing of medical concepts and enhancing the overall semantic coherence of transcribed dialogues. These findings illustrate the dual role of LLMs in augmenting AST outputs and increasing the accuracy and efficiency of transcription tasks. This integration of LLMs adapted for medical applications is reported to enhance the accuracy of transcribing data in medical contexts [86,87] and reduce the time doctors or physicians need to input the documentation. Jelassi et al. [88] demonstrated the use of French language ASR in healthcare by finetuning the Whisper Large-v2 model targeting the need for transcribing radiology data.

In this use-case, we have seen solutions that leveraged contextual generative AI to provide more personalized care, enhancing patient care by adapting interventions to individual needs and preferences. This approach not only improves the quality of care but also fosters a deeper connection between virtual or physical caregivers and patients, ultimately leading to more effective and compassionate healthcare delivery.

4.2. Generative AI applications in the medical sectors

Generative AI is transforming our world in a positive way and the sectors it concerns cover a wide range of application domains [89]. The use of generative AI in the medical domain and healthcare is also fast-paced [90]. As generative approaches are previously often used to understand the hidden implication or structure of data, generative AI can also be used to provide coherent explanations of medical data, thus enabling better understanding and interpretation both for medical staff and patients. Oftentimes, generative AI can be leveraged to generate new ideas and propose novel medical treatments or advice.

Regarding the insufficient provision of patient care and alleviation of the workload on medical practitioners, generative language models serve a crucial function. One such model, Med PaLM [91], is an LLM capable of generating medical responses that are equally proficient and empathetic as some medical experts but still inferior to clinicians. Med PaLM is a finetuned version from Google PaLM [92] (a 540-billion parameter LLM) trained on multiple large medical scopus and language tasks, like MedQA [93], MedMCQA [94], PubMedQA [95] and Measuring Massive Multitask Language Understanding clinical topics (MMLU) [96]. When posed with questions structured similarly to those found in medical licensing exams in the USA, Med PaLM demonstrated a 17 percentage points higher accuracy in responses compared to other evaluated language models. This assessment, conducted by a research team from Google and DeepMind, was published in Nature [91].

Hadid et al. [97] applied generative AI to enable unobtrusive health diagnosis by automatically extracting meaningful correlations between changes in facial characteristics and expressions with internal health conditions or emotions. The authors aim to combine computer vision techniques with the power of generative AI to accomplish this targeted task of knowledge extraction for visual medical diagnostics. They also explored the ability of generative AI for data augmentation while preserving the true characteristics of the data and ensuring privacy. This work is based on the main assumption that faces can serve as indicators of various health-related conditions. For example, research has linked eye movements to the diagnosis of Parkinson's disease [98] and identified distinct facial features that help in recognizing children with autism [99].

Verbal communication empowered by generative AI tools like ChatGPT can be used to enhance robot–human interactions in real-life situations and health care. This constellation also provides great potential for researching social interaction between the elderly population and robots and to investigate how social robot perceives their environments and respond to them. A recent research article by Sabo et al. [100] explored the ability to use the social robot called Furhat for screening Alzheimer's disease. User acceptance test is conducted on attendees from both a large science fair and a scientific conference revealing more positive acceptance among the older subjects compared to younger ones [100].

In this use-case, generative AI in the forms of GPT models finetuned on medical data is used to assist decision-making in medical diagnostics or extracting meaningful clues between medical conditions and visual facial changes. We have seen solutions that leveraged language generative AI to provide sophisticated and specialized assistance in medical care, enabling more accurate diagnoses, personalized treatment plans, and efficient management of patient records. These advancements demonstrate the potential of generative AI to enhance the capabilities of healthcare professionals, reduce administrative burdens, and improve overall patient and treatment outcomes.

4.3. Generative AI serving for people with disabilities and impairments

Generative AI, with its rapidly evolving capabilities, has demonstrated its potential to revolutionize the assistive systems available to individuals with disabilities and impairments [101]. By creating adaptive and intelligent tools, generative AI can address various challenges faced by people with physical, cognitive, and sensory disabilities.

Qin et al. [71] emphasized the necessity of timely intervention for children with speech problems to mitigate the negative effects these deficiencies can have in adulthood. A long-term study of over 30 years by Elbro et al. [102] indicated that children with specific language impairment (SLI) at younger ages are significantly more at risk of social isolation, academic challenges, and an increased likelihood of unemployment. However, such interventions are often delayed due to the high cost of speech services and the shortage of speech and language pathologists (SLPs) [103]. To address this issue, Qin et al. [71] proposed a generative AI-supported tool designed to assist caregivers in evaluating children's phonological development, support SLPs in lesson preparation, and alleviate the severe shortage of SLPs.

Tang et al. [72] proposed a system called EmoEden using generative AI to learn and understand the emotions for children with high-function autism (HFA). Children with HFA often have difficulties in recognizing emotions and expressions from their social interaction partners thus causing emotional distress and social difficulties. Previous solutions integrated into the conversational agents' often lack the ability to effectively and dynamically learn contextual content. Recent advances in generative AI techniques, with the capability to generate both high-quality texts and visual contents provide a promising way to help develop social conversational, personalized intervention, and assistive agents in helping children with HFA to better learn and understand emotions and generate contextual relevant expressions [104]. As presented in their field study [72] conducted with 6 HFA children showed promising results by demonstrating improved emotional recognition and expression skills, but also revealed potential risks of such systems over a test period of 22 days.

Upadhyay et al. [105] highlighted the assistive potential of generative AI, exploring its use in developing training systems for employees with special needs. In their review, the authors emphasized the vast opportunities for designing personalized learning solutions through generative AI methods. These solutions can be tailored to accommodate the unique needs of employees with physical or cognitive disabilities. The AI-based solutions support special learners by customizing assistive technology and content according to the level of disability and individual needs. The paper also emphasized the critical importance of collaboration between training departments, government agencies, and technology solution providers.

In this subsection, we have focused on the interaction between generative AI and humans as a use-case. However, this technology can also fulfill its core generative purpose by creating synthetic data, which can enhance the training process for developing more robust systems aimed at assisting people in need. A Brain–Computer Interface (BCI) is a technology that enables direct communication between the brain and external devices, allowing control by individuals with physical disabilities. As an assistive technology, BCIs hold great promise, but they face numerous technical and data-related challenges that hinder their practical use [106]. A major challenge is the scarcity of data and its strong inter-subject variability. Eldawlatly et al. [107] addressed this challenge by applying generative AI methods for data augmentation to enhance model generalization across different users. Using various GAN-based approaches, they reduced the subject-dependent issue by incorporating synthetic data into the limited real training data without significantly compromising accuracy.

In this use-case, the generative AI is used to build adaptive conversational agents able to assist children with autism, and a GAN-based approach is used for data enhancement in biometric data. We have seen solutions that leveraged generative AI (in text and visual outputs) to serve people with disabilities and impairments, enhancing accessibility through personalized communication tools, adaptive interfaces, and intelligent assistive devices. These innovations have the potential to significantly improve quality of life, providing earlier interventions for children with speech disorders, and enabling higher independence and participation in daily activities for individuals with diverse needs.

4.4. Generative AI serving for people looking for more comfort

Social isolation and loneliness in older adults are becoming a prominent problem in our society [108]. With the tremendous improvement in the medical and healthcare domains, elderly people now live longer but are more exposed to the risk of living alone and at the risk of being socially isolated [109]. There are several studies [110–112] on exploring how loneliness would affect mental health, such as depression [113], anxiety, and cognitive decline [114]. Therefore, it is important with the new disruptive technology such as generative AI to find a way to address this pressing and challenging issue.

A conceptual study by Pani et al. [115] explored the potential of using generative AI, such as chatbots, to provide social support and alleviate loneliness. The authors reviewed prominent areas where AI chatbots are currently employed and compared intelligent chatbots designed for social companionship with those created specifically for assistance. Ethical considerations and limitations of integrating AI chatbots were discussed, and promising future use-cases were proposed.

Griffith et al. [116] advocated for the use of generative AI to enhance AI-assistive technology through personalization in their concept paper. They propose fine-tuning existing generative models using limited training data derived from text, audio, and visual records of target individuals to create customized user experiences, which can then be integrated within the end-user's technology ecosystem. This conceptual work [116] aims to promote systems using generative AI to enable various practical applications, such as generating full-scale behavioral digital twin models for individuals with limited training data and providing dedicated and more personalized assistance.

Not only elderly people feel a sense of loneliness, research also focuses on the causes and consequences of loneliness in the workplace [117,118] and strategies are developed to foster a more connected working place to reduce the feeling of individual isolation and loneliness at the workplace. A study by Ozcelik et al. [119] showed a significant relationship between employees' performance and loneliness and that greater workplace loneliness results in lower job performance. Deniz et al. [120] demonstrated such a problem for private hospital employees and found a direct causation between loneliness in the workplace and negative job performance.

Therefore, generative AI can be used as a creative companion [121] to enhance creative thinking and work productivity and to foster new styles of work by bringing people together and reducing the feeling of loneliness at workplaces. A recent study by Xie et al. [122] looked at 1155 undergraduate students and their use of robots for learning. The study went over a 1-year period and included three rounds of surveys. They investigated the impact of interaction frequency with chatbots on the student's learning autonomy under two different aspects which are virtual companionship and knowledge acquisition. They highlighted the impact of interaction frequency with chatbots on learning autonomy, revealing that social presence plays a key mediating role. For learners seeking virtual companionship, increased chatbot interactions indirectly enhance learning autonomy. However, for those focused on knowledge acquisition, frequent interactions with chatbots negatively affect both social presence and learning autonomy, although a strong social presence can help mitigate these negative effects. This study offers new insights into optimizing generative AI tools for diverse learning preferences in educational settings.

Recently, using GitHub Copilot also shaped the way how simple programming problems are solved [123]. By engaging with employees in collaborative problem-solving, Copilot can simulate a virtual co-worker, offering suggestions, generating ideas, and even providing feedback on creative coding projects. This interaction can help alleviate feelings of isolation, especially in remote or solo work environments, by fostering a sense of partnership and collaboration, ultimately contributing to a more connected and supportive work experience. Puryear et al. [124] published a work investigating the use of Github Copilot in college classrooms. It found out that Copilot is able to solve introductory assignments for introductory computer science and data science courses. The AI-generate code is mostly unique and can reach certain levels of correctness, style, and skill level appropriateness, leading to human-graded scores ranging from 68% to 95%.

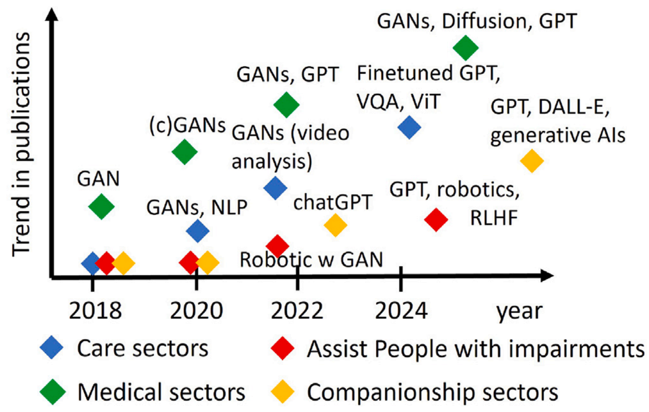

Fig. 2. visualized the trend of generative AI's use in assistive technologies, mainly in research (diamond), using the classification scheme made in Section 4. Disclaimer: This graph is not exhaustive. We have reviewed the published articles to the best of our ability.

Seymour et al. [125] developed the concept of multi-user conversational user interfaces by expanding beyond the single-user-single-device use-case of current LLM applications. They envisioned these conversational interfaces as assistive tools that integrate smoothly into discussions, avoiding rigidity or bossiness, and instead fitting naturally into human communication processes. These interfaces aim to enhance decision-making, encourage participation and contributions, and perform summarization tasks. Consequently, such systems can improve collaboration and foster creativity.

In this use-case, multimodal LLMs are used in building customized assistive companions. We have seen solutions that leveraged generative AI (in text, image, video, and audio) to serve people in terms of companionship and co-creation, offering more personalized interactions, emotional support, and collaborative creativity. These AI-driven tools can strengthen social connection, and stimulate creative expression, and address both emotional and practical needs in a wide range of contexts.

In this section, we discussed the use of generative AI in four key areas of assistive systems. In Fig. 2, we visualize the trend of publications over the last decade using generative AI in its respective research domains applying the same classification scheme as provided in this section. These trends also highlight the limitations that hinder the deployment of generative AI in assistive technologies, such as lack of explainability, bias issues, ethical and regulatory complexities, and varied acceptance levels. We will discuss these limitations later and explore their correlations, as shown in Fig. 2.

5. Technology stacks of generative AI used for assistive systems

In this section, we consider the kind of methodologies or technical stacks that leveraged generative AI for assistive systems. The technological stacks are grouped into three main use-cases where they are applied.

5.1. A human-like ChatBot

ChatBots based on LLMs are used for communicating with customers, caregivers, caretakers, or patients. The technology stacks of LLMs encompass several critical components. In the training stage, extensive and diverse text data is collected, cleaned, and tokenized. In the scope of medical use or care-sectors specific text corpus are required. These copora are built often from medical context or other specific domains beyond the general common knowledge basis. The core model architecture is typically based on transformers [58], utilizing self-attention mechanisms and feed-forward neural networks. Training these models requires substantial computing power, often leveraging GPUs [126], TPUs [127], and distributed computing frameworks [128]. Wei et al. [129] looked at the emergent abilities of LLMs. The authors demonstrated the power of finetuning based on large-scale foundation models. Evaluating these models requires metrics like perplexity and fine-tuning with domain-specific data. The current deployment also involves model compression [130] and inference engines to ensure efficiency, supported by APIs for integration [131]. Throughout the designing process of LLMs, security and compliance measures, including data privacy, bias mitigation [27], and compliance with ethical guidelines, are essential.

As an example of such LLM-based chatbots, Montagna et al. [132] utilized one to assist chronic patients in performing autonomous self-management. The authors highlighted the advantages of LLMs in aiding patients with chronic conditions, such as tracking blood pressure, adhering to medication schedules, and responding to specific patient questions regarding their aggregated health data. In their proposed architecture, they also addressed the existing challenges of LLMs, such as GPT-4, particularly privacy and security concerns related to compliance with data protection laws, which is especially critical when this technology is used in the healthcare sector.

5.2. A good companionship

To build virtual or physical social robots interacting with people, several technologies are required. These technologies include, but are not limited to speech recognition [133] also possible in a clinical context, text, and visual understanding [134]. Physical assistive robots as demonstrated by Tytarenko et al. [85] can further leverage reinforcement learning strategies combined with generative approaches like diffusion transformers to develop smart policies for learning strategies.

One possible use-case of generative AI in forms of companionship is demonstrated by Xu et al. [134]. The authors looked at the specific requirements of leveraging LLMs as good companions. To enable human-like companionship, these systems should operate based on personalized, real-time, and evolving knowledge of their users. Utilizing an eyewear device, the authors captured visual and audio signals from the user to extract real-time contextual semantics and generated a user profile. This profile includes historical contexts and real-time semantics, which can evolve over time. This personalized knowledge helps LLMs generate output that is converted to audio and spoken to the wearer when appropriate. A small field study [134] demonstrated the progressive development of their proposed system, leading to a better understanding of its users. To capture real-time semantic context, one can use a vision-to-language model, such as LLaVA [63], and a speech recognition model like Whisper [135].

One question that needs to be addressed is how generative AI can be used to develop better companions. As previously discussed, recent trends focus on using multimodal LLMs to create systems with a better understanding of the world. One possible multi-modality as introduced by Xu et al. [134] leveraged the vision-to-text model combined with speech recognition. A typical vision-to-text model combines computer vision and NLP techniques to generate descriptive text from images [136]. This process typically involves two main components including an image encoder and a text decoder. The image encoder is typically a ResNet50 model [137] that extracts visual features from the input image. These features are then fed into the text decoder, which is usually a recurrent neural network (RNN) or a transformer model [58], to generate a coherent and relevant textual description. The training is based on large datasets containing images paired with descriptive captions, allowing it to learn the associations between visual elements and corresponding text descriptions. This technology is widely applied in areas such as automatic image annotation or accessibility for visually impaired users. Typical models from this category account LLaVA [63] combining a vision encoder followed by a GPT-4 for general purpose visual and language understanding, CLIP [136], or SimVLM [138] which uses a vision transformer instead of a CNN as the encoder.

One example of speech as input modality can be processed with Whisper [135] which is an automatic speech recognition system introduced by OpenAI and published in September 2022 as an open-source software. It utilizes an encoder–decoder transformer-based architecture, similar to those applied in LLMs, to process audio inputs and convert them into text. The model is trained on a diverse and extensive dataset of audio recordings paired with corresponding transcriptions in a weakly supervised manner, enabling it to recognize speech with high accuracy across various accents, dialects, and noisy environments. The resulting models demonstrated good generalization ability and performed competitively with similar models that were trained using prior knowledge and full supervision, without requiring any dataset-specific fine-tuning. Whisper is thus robust to handle different languages and contexts, making it highly adaptable and effective for real-time applications, such as virtual assistants, transcription services, and accessibility tools for individuals with hearing impairments. Combining the collective power of complementary multi-modal input sources, system developers are able to design good social, virtual, or physical companions able to truly understand the needs of the people they are interacting with.

5.3. Creative co-working and collaboration

Creative co-working and collaboration involve the process of individuals or teams working together to generate, refine, and execute innovative ideas. Typical representatives enabling this creative task to use text-to-image [139–141] or text-to-video [142–144] models, which can generate images from textual descriptions by using advanced deep learning techniques. These models typically employ a generative approach, where the input prompts are first encoded into a meaningful representation using NLP techniques. This step can be realized using the CLIP [136] model, among other possibilities [145]. This encoded representation is then fed into a generative model, such as GANs or Diffusion Models, which synthesize images or image sequences that match the given textual description. The result is the ability to create diverse and high-quality images based on text prompts. Thus these image, video [146], audio [147] generation models can be leveraged in diverse applications e.g. art creation and design, marketing and advertising, film production, entertainment, and education to enhance accessibility and aiding in visualization tasks. More commercialized models in this creative field are DALL-E [2], Stable Diffusion [3], Midjourney [4], or other recently proposed vision transformer systems on Hugging Face.

Another collaborative tool is represented by the project GitHub Copilot,[1] developed by GitHub in collaboration with Microsoft and OpenAI, is an AI-driven code completion tool designed to assist developers. Seamlessly integrated into IDEs, Copilot can be installed as an extension within the coding environment. At its core is the GPT-3 [1] model, trained on a vast dataset of public code repositories. As developers write code, copilot analyzes the context and the existing code, to generate relevant suggestions aligned with the developer's intent. It provides real-time assistance and learns from human feedback. With human feedback, it allows the model to adapt to human preferences over time. By automating routine coding tasks and offering build-in, instant suggestions, Copilot can enhance developer productivity, enabling users to focus on more complex and creative aspects of their coding work and provide a sense of companionship and collaboration, especially in remote or solo work environments.

In this paragraph, we have seen hyped generative models used to foster collaboration and creative co-working. This demonstrates the potential of generative models to enhance teamwork and drive innovation by enabling more effective collaboration and creative synergy.

[1] GitHub Copilot: https://copilot.github.com/

6. Discussion and limitations

In this section, we discuss the current limitations of using generative AI in assistive technologies from various aspects. Both the legal and technical aspects of these system restrictions are taken into account here.

6.1. Governmental undertaken on regulating generative AI on assistive systems

The EU AI Act, which is now in force starting from the first of August 2024, focuses on categorizing AI systems [148] according to their associated risks and corresponding compliance frameworks. Among these AI-based systems, generative AI systems have emerged as a particularly debated category due to their widespread adoption in various domains of our daily lives, presenting heightened concerns regarding risks and breaches, particularly concerning individuals with disabilities and impairments.

One joint effort involving governments and several known multinational agencies and UNESCO are focusing on producing reports [149], sets of recommendations [150], and guidelines [151] that outline the utilization of generative AI in specific domains like education, healthcare, and the workplace. Some of the guidelines in [151] include ensuring proper inclusion and equity, continuously monitoring and validation of generative AI systems, incorporating diverse perspectives and expressions of ideas, and assessing long-term implications in an intersectional and interdisciplinary approach.

The EU imposes strict regulations on the most high-risk AI models [152], with violations potentially leading to substantial fines of up to 35 million euros or 7% of a company's annual revenue. Generative AI in assistive systems would be considered among the highest-risk applications in this regard. Therefore, complying with governmental regulation not only saves the company's money, but also is essential to ensure safety, reliability, ethical standards, and legal compliance. Some first steps are already made in this direction, but much more needs to be done to sustain the long-term development of generative AI in the field of assistive systems.

6.2. Missing evaluation metrics for free-form text

To access the output of ChatGPT or other generated text outputs, evaluation metrics for free-form text are necessary. Free-form text answers generated by generative AI are responses that are not constrained by a predefined format or structure. Instead, these responses are created dynamically, based on the text prompts it receives. These answers can range from simple sentences to complex paragraphs. Unlike constraint answers, free-form text allows for more nuanced and human-like outputs. A large challenge lies thus in the evaluation of such free-form text answers, especially for tasks associated with assistive AI technologies. In assistive systems, where these responses may be used in sensitive contexts such as healthcare, education, or personal assistance, reliable evaluation methods are crucial to ensure that the model provides meaningful, accurate, and supportive interactions. Without proper evaluation, the risk of misleading or inadequate assistance increases, potentially undermining the system's effectiveness and user trust.

For general-purpose foundation models, such as LLMs, standardized tests to evaluate them for specific purposes are already established. For example, one benchmark is the Massive Multitask Language Understanding (MMLU) dataset [96], which includes multiple-choice questions across 57 disciplines including math, philosophy, and medicine, to assess LLM outputs. Additionally, tools like LMSYS Chatbot Arena [153] are used, in which the answers of two LLMs are played off against each other for human evaluation, and OpenAI's HumanEval [154], that assesses the code generation capabilities with Copilot and is also used to incorporate human feedback. Other large-scale benchmark framework like HELM [155] has been proposed to evaluate foundation models across various scenarios, metrics, and models, including support for multi-modality and model-graded evaluation.

However, there are currently no widely recognized benchmarking datasets or tools for evaluating generative AI in assistive systems. In the annals of internal medicine, Dr. Omiye et al. [156] clearly emphasized these LLMs' pitfalls of using such text generative models in health systems and stresses the demand for health care professionals to familiarize them with the rapidly changing landscape of LLMs in medicine. Shah et al. [157] also criticized the issue of missing standardized ways to evaluate and quantify the benefits of LLMs under clinical settings [158].

The absence of widely recognized benchmarking datasets or standardized evaluation tools for generative AI in assistive systems poses significant challenges to their deployment. This gap hampers the ability to assess and validate the performance, reliability, and safety of these AI-driven solutions in critical areas such as healthcare and medical contexts. Without robust benchmarks, it is difficult to ensure that these AI systems meet the necessary standards to support healthcare professionals and patients effectively.

6.3. Bias in large language models and its harms

Bias is a common problem in both generative AI models and general AI models. Since LLMs are learned from human produced text and materials, they tend to learn patterns of human biases or other harmful attitudes in the data [159], which could lead to real-world harm [160]. Results produced from biased data may express these biases in various ways, for example by providing sub-optimal recommendations, failing to recognize or respect cultural differences, or reinforcing stereotypes. Therefore, disseminated language model generated text should be reviewed and noted that they could contain human-like biases or stereotypes [161]. Bias in generative AI can significantly impact assistive systems, potentially leading to biased, inappropriate, or even harmful outcomes for users. Given that these systems often serve vulnerable populations, such as individuals with disabilities, cognitive impairments, or those requiring personalized care, the presence of bias can exacerbate existing inequalities and hinder the effectiveness of the assistance provided.

Despite the promising potential of chain-of-thought prompting to enhance the reasoning abilities of LLMs, the study by Turpin et al. [162] revealed that this method can still be systematically unreliable due to distinct biases. Through extensive experiments, the authors demonstrated that these step-by-step explanations can often be incorrect and misrepresent the true reasons behind a model's predictions when biased features are added to the inputs. When models are inclined toward incorrect answers, the explanations often attempt to justify those answers. When models generate incorrect answers but attempt to justify them through flawed reasoning, the risk of harm increases, particularly for vulnerable populations relying on assistive technologies. The presence of bias not only skews the outputs but also compromises the integrity of the explanations provided by the AI, making it challenging to trust these systems.

Addressing bias is essential to ensure that assistive systems are less biased, more inclusive, and capable of providing high-quality support to all users, regardless of their background or characteristics. It thus requires careful consideration of the data used to train these models, continuous monitoring for biased outputs, and incorporating diverse perspectives during the development process.

6.4. Missing transparency

One major challenge of large and complex deep learning models is the lack of transparency [163] regarding how these models reach certain decisions. LLMs like GPT-3 face several challenges related to missing transparency due to the complexity of their internal architectures, lack of interpretability, and their "black box" nature [29]. This missing transparency makes it difficult to understand how specific inputs are processed to produce outputs. This complexity can obscure the decision-making process and raise trust issues in crucial domains, especially in healthcare sectors, where medical decisions are directly linked to human well-being. However, recently there have been researched strategies to improve the decision-making process in LLMs including enhancing data quality [164], refining model architecture, finetuning or distillation to specific use-cases [165] and incorporating better evaluation techniques. Graph-based LLMs [166] also offer a promising direction towards this issue.

Unlike traditional algorithms where the logic can be traced and understood, the deep learning processes in LLMs are not as straightforward to decode and interpret [26]. The current trend of research encourages to use of chain-of-thought (CoT) prompting approach with LLMs to better understand the human inputs [167,168]. The CoT prompting in LLMs refers to a technique where the model is prompted to generate a sequence of intermediate outputs leading up to a final answer, rather than producing an immediate response. This approach can help improve the model's performance on complex tasks by breaking down the problem into more manageable parts. Cohn et al. [169] leveraged the CoT prompting approach to build an assistive tool in an educational context combined with LLMs to assess students' responses to middle school science subjects, e.g. Earth Science, and assess their true understanding of the matter.

As users and even developers may not fully understand how a generative model arrives at a particular result, it may raise concerns about trust, accountability, and reliability, especially under medical contexts [170,171]. These issues underscore the need for ongoing research to improve the interpretability and transparency of such generative AI systems, as well as for the development of robust frameworks for explaining generative AI's behavior. This is particularly important in the medical field, where it is essential for practitioners and doctors to trust that the AI's recommendations are as understandable and reliable as those provided by their human colleagues.

6.5. Generative model is still missing true human understanding

Richard Feynman once said, "What I cannot create, I do not understand" [172]. Generative AI models, such as GPT-3 [1], are designed to generate coherent and contextually relevant text based on the input they receive. However, these models often excel more at generating text than truly understanding the content [173]. This phenomenon is called the paradox hypothesis of generative AI. Recent research by West et al. [173] considered precisely this exact issue. It indicates that the generative capability of these models appears to be more effective than understanding, which contradicts human intelligence, where generation is typically considered more challenging.

This study by Hendrycks et al. [96] examined the strengths and limitations of GPT-3 across a range of tasks, such as elementary mathematics, US history, computer science, and law. Although the GPT-3 model enhances accuracy by nearly 20% over random chance on average, it still requires significant improvements to reach expert-level accuracy on certain tasks. The research underscores areas where GPT-3 lacks true understanding and often fails to recognize its own errors. Dakhel et al. [174] also demonstrated that GitHub Copilot lacks the capability to integrate information from various sources to produce a cohesive solution.

Thus, it may still be difficult for these generative AI systems to reach human-level or expert-level understanding. In summary, the inability of generative AI to produce human-like understanding can lead to miscommunication, reliability issues, limited usefulness, poor user experience, and reduced problem-solving abilities. This reduced problem-solving ability and lack of true understanding mean that generative AI might offer solutions that are irrelevant or even harmful, particularly when assisting individuals with disabilities or impairments who rely on precise and empathetic responses.

6.6. Potential misinformation and manipulation

LLMs, such as GPT-3.5, LLaMA, and PaLM, have demonstrated significant knowledge and expertise across various tasks. However, their generated responses cannot be entirely trusted due to the phenomenon of hallucination [28], where LLMs can generate fictitious information that appears plausible to users. The underlying causes of this issue and its widespread occurrence are still unclear [175]. The phenomenon could be a useful feature in creative writing, but on the other hand can raise severe risks in many application areas, such as law enforcement, politics, media, and medical decision-making.

Previous works looked at this problem from various perspectives, ranging from overfitting [176] to memorizing effect [177]. Yao et al. [175] investigated the effect of directly triggering the LLMs to fabricate non-existent facts or inappropriate information by prompting the network with constructed non-sense Out-of-Distribution terms composed of random tokens. They consider this form of attack similar to an adversarial attack against the LLMs.

Despite the benefits of generative AI tools in building assistive systems, it still remains unclear what are the negative impacts of the hallucination effects of LLMs on these systems. One example is the use-case of the generative AI tools in supporting children with high-functioning autism (HFA) as investigated by Tang in [72]. In interviews with parents whose children participated in the study [72], concerns were raised and a desire to monitor the content of conversations was expressed by most of the parents. Given the complexity and sensitivity of this issue, it is insufficient to claim that assistance systems equipped with powerful LLMs can replace human intervention. The study in [178] assesses how students utilize generative AI for various purposes in their daily lives, with 29 percent indicating that they use it to manage anxiety or mental health issues. This suggests that, even in personal settings, the generation of inaccurate or misleading information by these AI systems can have serious negative effects. To ensure more effective collaboration between AI-assisted systems and human interaction, it is crucial to emphasize the balance between AI-based training and face-to-face communication.

Thus, it is essential to mitigate the risk of hallucinations and adversarial attacks to ensure the reliability of generative AI systems for sensitive applications, such as summarizing medical records, medical decision-making, producing financial analyses, and offering legal advice as presented by Tonmoy et al. [179].

6.7. Privacy and ownership

Numerous studies investigated the potential risks of incorporating generative chatbots into everyday life, with a primary focus on security, privacy, and ethical concerns [180–183]. As an example the regulation of OpenAI's handling of personal information claims to be in compliance to the privacy laws of various countries [180]. For example, the General Data Protection Regulation (GDPR) in Europe, enacted in 2018, has enhanced data protection rules for individuals within the European Union (EU). Although OpenAI claims to adhere to GDPR and other relevant laws as outlined in their privacy policies, these measures may still not fully alleviate individuals' privacy concerns, such as the storage and handling of their personal information by OpenAI [180].

Unresolved copyright and intellectual property issues [184] surround content generated by generative models, such as new medical images. Questions arise regarding who should own the copyright to AI-generated content and who should be held liable for any harm it might cause. These issues become more complex when AI-generated content is based on existing copyrighted materials [185].

Therefore, declaring ownership of AI-generated content is important to establish clear intellectual property rights, ensure accountability for the content they produce, and address potential legal and ethical issues, such as copyright infringement and liability for any harm caused by AI-generated content. This clarity is essential for fostering trust and transparency in the use of generative AI technologies. This also relates to the use of generative models in terms of creative companionship and collaboration tools to assist people at the workplace.

6.8. Complexity and resistance of integrating generative AI in assistive technologies

Yonah Welker has written an article as part of the AI Governance Summit published on the World Economic Forum [186] in which he emphasizes the importance of policy and regulation in shaping the use of generative AI in assistance systems to reach its fullest potential. While generative AI holds significant promise for enhancing inclusion and empowerment for individuals with cognitive disabilities, it still demands interdisciplinary collaboration and close partnerships within these multi-stakeholder scenarios, which include families, caregivers, developers, and the targeted users simultaneously.

Due to the identified limitations in previous subsections, it remains challenging to seamlessly integrate these technologies into assistive technologies for real-life use-cases. In interviews with parents whose children participated in the study [72], most parents expressed strong concerns and raised the desire to monitor the content of conversations conducted between the generative AI-assisted interaction tool and children with autism.

Currently, there is no consumer acceptance model specifically for generative AI devices in service delivery, unlike the general AI device use acceptance model (AIDUA) proposed by Gursoy et al. [187]. However, with the rapid advancements in generative AI and its growing presence in everyday life, there is a clear need to extend these acceptance frameworks to include generative AI and its unique applications. Such an extension would need to incorporate aspects like novelty value, perceived humanness, and cognitive attitudes to address the distinct characteristics of generative AI. Initial efforts in this direction can be seen in the study by Ma et al. [188], which explored the willingness to adopt ChatGPT in the chatbot application. They collected 500 questionnaires from participants familiar with ChatGPT and found that during the initial evaluation phase, factors such as social influence, novelty value, and perceived humanness positively influenced individuals' perceptions of ChatGPT's performance and expectancy. They also found that age negatively correlated with willingness to embrace this technology.

6.9. Integration limitations regarding computing power, data storage and scale

The deployment of generative AI in assistive technologies can often be streamlined by integrating pre-existing LLMs with minimal training effort to provide personalized care [105] or human-like interactions in service and care sectors [83]. Rather than building models from scratch, these LLMs can be fine-tuned on domain-specific datasets, enabling them to adapt to the unique characteristics and requirements of particular use cases [88]. This approach significantly reduces the computational and time investment needed for training, focusing instead on optimizing and customizing the models for effective application in targeted assistive technology scenarios.

A significant challenge in deploying generative AI in assistive technologies is the lack of sufficient data in specific domains. Many specialized fields lack the extensive datasets needed to effectively train models [88], leading to limited performance and generalization issues. Furthermore, existing models often do not scale well, struggling to maintain efficiency and accuracy when adapted to diverse and highly specialized tasks [189]. This hinders the broader applicability and reliability of generative AI solutions across various assistive technology domains.

These systems involve data that might be categorized as sensitive personal data, such as health records or medical information, raising significant privacy and security concerns. Storing and managing this data securely is critical, as any breach could lead to serious consequences for individuals' privacy and trust. Ensuring compliance with data protection regulations, such as GDPR in Europe and Health Insurance Portability and Accountability Act (HIPAA) [190] in the

Table 1
Overview of the works investigated in this survey. They are summarized to reflect the different aspects considered in this work, such as category of use-cases, characteristics used in the assistive technologies, potential aspect of limitations, generative models used, and the kind of data generated by these models.

Work	Category of use-case	Characteristics	Potential aspect of limitations	Generative models used	Kind of generated data
Nugent et al. [21]	care sectors	co-creation & collaboration	bias, missing true human understanding	LLMs for text	adaptive text for care sectors
Revell et al. [83]	care sectors	companionship robots	bias, lack of Transparency, privacy concerns	LLMs for text	niche text for care sectors
Tytarenko et al. [85]	care sectors	companionship robots	bias, lack of understanding and transparency	diffusion models for actions	learning smart policy for agents
Adedeji et al. [86]	care sectors	co-working system	bias, potential misinformation	speech-to-text model	automatic transcription to text
Singhal et al. [91]	medical sectors	co-creation & collaboration	bias, lack of understanding and transparency	LLMs for text	medical text for diagnostics
Hadid et al. [97]	medical sectors	co-creation & collaboration	bias, lack of understanding and transparency	GAN for visual data augmentation	synthetic visual outputs
Sabo et al. [100]	medical sectors	chatbot & collaboration	bias, lack of transparency, misinformation	speech recognizer, ChatGPT, speech synthesizer	human-like speech interactions
Montagna et al. [132]	medical sectors	companionship & collaboration	bias, misinforamtion, lack of transparency	LLMs like GPT-4	personalized management plans
Qin et al. [71]	supportive sectors	companionship & collaboration	bias, misinforamtion, lack of understanding	speech recognizer, LLMs	human-like dialogues
Tang et al. [72]	supportive sectors	companionship & collaboration	bias, misinforamtion, lack of understanding	emotion recognition, speech-to-text, Azure's text-to-speech	immersive learning context
Yue et al. [104]	supportive sectors	companionship & collaboration	bias, misinforamtion, lack of understanding	GPT-3.5 and GPT-4	text for story telling and social emotional learning
Upadhyay et al. [105]	supportive sectors	companionship & collaboration	bias, misinforamtion, lack of understanding	review different GenAI tools	d develop adaptive learning strategies
Eldawlatly et al. [107]	supportive sectors	co-working system	bias, lack of understanding and transparency	GAN for data augmentation	synthetic output EEG signals
Xu et al. [134]	supportive sectors	companionship & collaboration	bias, misinforamtion, lack of understanding	customized LLM chatbot	speech to instruct users over eyewear
Pani et al. [115]	comfort sectors	companionship & collaboration	bias, misinforamtion, ethical considerations	ChatGPT, Bard	human-like dialogues
Griffith et al. [116]	comfort sectors	companionship & collaboration	bias, misinforamtion, ethical considerations	LLMs like CareCall, text-to-speech like VALL-E,	image generation for avatar develop behavioral digital twins
Xie et al. [122]	comfort sectors	co-creation & collaboration	bias, misinforamtion, lack of understanding	customized chatbot Benny for text input (LLMs)	human-like dialogs with knowledge transfer
Puryear et al. [124]	comfort sectors	co-creation & collaboration	bias, misinforamtion, lack of understanding	Copilot for coding	improved coding skills
Seymour et al. [125]	comfort sectors	companionship & collaboration	bias, misinforamtion, lack of transparency	LLMs for multi-user-sessions	human-like dialogues

US, is essential, alongside implementing robust encryption and access control measures to safeguard personal information throughout the data life-cycle.

In Table 1 we provide an overview of all investigated works in this comprehensive survey summarizing different aspects including the targeted category of use-case, the characteristics used as assistive systems, the potential aspect of limitations if appropriate, the generative models used and the kind of generated data it outputs.

7. Future directions

Possible future directions using generative AI in assistive systems are foreseen to include and extend the use-cases we have already identified in Section 4. These directions encompass e.g. enhanced accessibility by improving communication tools for people with disabilities, such as advanced text-to-speech and speech-to-text systems. Additionally, more intuitive interfaces for individuals with mobility impairments can be designed. Companion robots and virtual assistants are designed to provide assistance to the elderly or individuals with their daily tasks, like medication reminders, and social companionship. Furthermore, generative AI can support individuals or groups of individuals in creative fields in terms of co-working services such as writing, music creation, and art production by providing inspiration, drafting initial concepts, and enhancing creative outputs to enhance workplace productivity and reduce workplace loneliness.

Currently, it is also promising to work on the discussed limitations from Section 6. Proper and clear government regulations are required to establish legal frameworks for the development and use of generative AI technologies in assistive systems. Standard benchmarking for evaluating these systems is essential for comparative solutions, ensuring consistency in performance metrics, facilitating objective assessment, and driving advancements through clear and quantifiable goals. Reducing the inherent bias issue and improving the explainability and transparency in such systems make them more trustworthy and reliable. A clear declaration of ownership of AI-generated content further sets a legal foundation for resolving issues related to intellectual property, accountability, and the responsible use of AI technologies in assistive systems. This is of importance, as these systems are used in areas where people are directly affected.

Here, we reviewed some concrete potential solutions or relevant paths to be explored to overcome some mentioned limitations. Promising research advancements have emerged in systems like Retrieval Augmented Generation (RAG) [191], which help mitigate hallucination in LLMs by incorporating external, relevant information. RAG works by retrieving pertinent data from a pre-defined knowledge base or external sources, allowing the model to generate more accurate and fact-based responses. By grounding LLM outputs in real-world, verified information, RAG reduces the likelihood of generating incorrect or fabricated content. This approach not only enhances the reliability of LLMs but also improves their performance in domains requiring precise and factual information, such as healthcare, education, and technical fields.

Beyond smart algorithmic design techniques like RAG structure, the quality and richness of data play a critical role in reducing bias and hallucination in generative AI models. Google's DataGemma [192], designed specifically to address hallucination challenges, grounds LLMs' output in real-world statistical data from Google's Data Commons.[2] Data Commons is a publicly available knowledge graph that include over 240 billion data samples across hundreds of thousands of statistical variables, sourced from trusted organizations such as the United Nations (UN), World Health Organization (WHO), and Centers for Disease Control and Prevention (CDC). By combining these robust datasets with advanced AI models, policymakers, researchers, and organizations could gain access to accurate, reliable insights, and further minimize hallucinations and biases in AI-generated content.

Another major drawback of synthetic datasets is that they often suffer from limited intra-class diversity and insufficient cross-class discrimination, resulting in suboptimal performance. To overcome this challenge in synthetic data generation, a solution was proposed in [50], where the generative latent space can be separated by class specific boundaries. By sampling further from these boundaries, the variation in the generated samples is increased. Following the same goals, Boutros et al. proposed a novel method denoted as IDiff-Face [55], which utilizes conditional latent diffusion models to generate synthetic identities with realistic variations. The identity condition is incorporated into the model by mapping the training images into a low-dimensional feature space and integrating this representation into the diffusion model's intermediate layers through a Cross-Attention mechanism. To introduce variability in the generated outputs, the authors employed a Contextual Partial Dropout technique, which selectively drops components of the identity context with a certain probability during training. Thus conditional control to diffusion models [193] can keep the generated output realistic by guiding the generation process with specific conditions or input data, such as class labels, images, or text prompts. These conditions provide additional context and constraints for the model, ensuring that the generated output aligns with the desired characteristics. During the denoising process in diffusion models, the conditions help the model learning to generate data that is more coherent and aligned with the expected real-world patterns, leading to outputs that are both plausible and contextually relevant.

We believe that it is only possible to build secure, faithful, and trustworthy generative AI systems for assistive technologies if all these challenges and limitations previously identified are properly addressed.

[2] Data Commons: https://datacommons.org/

8. Conclusion

Generative AI models have recently surged in popularity, significantly impacting various sectors of our daily life. This comprehensive survey highlights the increased application of generative AI within assistive technologies, benefiting a wide range of stakeholders including assistive system developers, medical practitioners, the care workforce, and individuals requiring care and support. We have explored current trends in applying generative AI across four key domains in assistive technologies including care sectors, medical sectors, aiding people in need, and co-creation or co-working.

We identified existing limitations of generative AI and its use in assistive systems, such as lack of transparency and interpretability, bias, and missing common benchmarks for evaluation and compliance with legal frameworks. The main differences between identified research trends involve shifts from generalized generative AI models to more domain-specific applications that prioritize human-centric design and trustworthiness, as well as the incorporation of multi-modal data to enhance system performance.

Key future research directions include the development of explainable generative AI models that allow for greater transparency and trust, enhanced methods for bias detection and mitigation, and the establishment of standardized evaluation metrics for AI-generated content. Additionally, further exploration is needed into collaborative AI systems that support dynamic interaction between humans and AI, as well as the creation of robust ethical guidelines and regulatory frameworks that safeguard the rights and privacy of all stakeholders. These efforts aim to refine the integration of generative AI in assistive technologies, making them more effective, reliable, and ethically sound.

CRediT authorship contribution statement

Biying Fu: Writing – review & editing, Writing – original draft, Conceptualization. **Abdenour Hadid:** Writing – review & editing. **Naser Damer:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

This research work has been funded by the German Federal Ministry of Education and Research and the Hessian Ministry of Higher Education, Research, Science and the Arts within their joint support of the National Research Center for Applied Cybersecurity ATHENE.

Data availability

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

References

[1] B. Mann, N. Ryder, M. Subbiah, J. Kaplan, P. Dhariwal, A. Neelakantan, P. Shyam, G. Sastry, A. Askell, S. Agarwal, et al., Language models are few-shot learners, 2020, arXiv preprint arXiv:2005.14165.

[2] DALL-E, OpenAI, DALL-E now available without waitlist, 2022, https://openai.com/index/dall-e-now-available-without-waitlist/. (Accessed 29 July 2024).

[3] Stability.ai, Stability AI, Stable diffusion public release, 2022, https://stability.ai/news/stable-diffusion-public-release. (Accessed 29 July 2024).

[4] Midjourney, @Midjourney, [Twitter] Twitter, We're officially moving to open-beta! 2022, https://x.com/midjourney/status/1547108864788553729. (Accessed 29 July 2024).

[5] K.-B. Ooi, G.W.-H. Tan, M. Al-Emran, M.A. Al-Sharafi, A. Capatina, A. Chakraborty, Y.K. Dwivedi, T.-L. Huang, A.K. Kar, V.-H. Lee, et al., The potential of generative artificial intelligence across disciplines: Perspectives and future directions, J. Comput. Inf. Syst. (2023) 1–32.
[6] A. Korinek, Generative AI for economic research: Use cases and implications for economists, J. Econ. Lit. 61 (4) (2023) 1281–1317.
[7] J. Qadir, Engineering education in the era of ChatGPT: Promise and pitfalls of generative AI for education, in: 2023 IEEE Global Engineering Education Conference, EDUCON, IEEE, 2023, pp. 1–9.
[8] Y. Wu, Integrating generative AI in education: how ChatGPT brings challenges for future learning and teaching, J. Adv. Res. Educ. 2 (4) (2023) 6–10.
[9] J. Gao, T. Shen, Z. Wang, W. Chen, K. Yin, D. Li, O. Litany, Z. Gojcic, S. Fidler, Get3d: A generative model of high quality 3d textured shapes learned from images, Adv. Neural Inf. Process. Syst. 35 (2022) 31841–31854.
[10] A. Karnewar, N.J. Mitra, A. Vedaldi, D. Novotny, Holofusion: Towards photo-realistic 3d generative modeling, in: Proceedings of the IEEE/CVF International Conference on Computer Vision, 2023, pp. 22976–22985.
[11] Y. Huang, J. Gesi, X. Hong, H. Cheng, K. Zhong, V. Mittal, Q. Cui, V. Salaka, Behavior-driven query similarity prediction based on pre-trained language models for e-commerce search, 2023.
[12] N. Wiratunga, R. Abeyratne, L. Jayawardena, K. Martin, S. Massie, I. Nkisi-Orji, R. Weerasinghe, A. Liret, B. Fleisch, CBR-RAG: case-based reasoning for retrieval augmented generation in LLMs for legal question answering, in: International Conference on Case-Based Reasoning, Springer, 2024, pp. 445–460.
[13] L. Jin, F. Tan, S. Jiang, Generative adversarial network technologies and applications in computer vision, Comput. Intell. Neurosci. 2020 (1) (2020) 1459107.
[14] F. Boutros, V. Struc, J. Fiérrez, N. Damer, Synthetic data for face recognition: Current state and future prospects, Image Vis. Comput. 135 (2023) 104688, http://dx.doi.org/10.1016/J.IMAVIS.2023.104688.
[15] B. Chen, Z. Wu, R. Zhao, From fiction to fact: the growing role of generative AI in business and finance, J. Chin. Econ. Bus. Stud. 21 (4) (2023) 471–496.
[16] R. Lopez, A. Gayoso, N. Yosef, Enhancing scientific discoveries in molecular biology with deep generative models, Mol. Syst. Biol. 16 (9) (2020) e9198.
[17] M. Karabacak, B.B. Ozkara, K. Margetis, M. Wintermark, S. Bisdas, The advent of generative language models in medical education, JMIR Med. Educ. 9 (2023) e48163.
[18] M. Grupac, A. Zauskova, E. Nica, Generative artificial intelligence-based treatment planning in clinical decision-making, in precision medicine, and in personalized healthcare, Contemp. Read. Law Soc. Justice 15 (1) (2023).
[19] Y. Bian, X.-Q. Xie, Generative chemistry: drug discovery with deep learning generative models, J. Mol. Model. 27 (2021) 1–18.
[20] F.A. Boujarwah, Nazneen, H. Hong, G.D. Abowd, R.I. Arriaga, Towards a framework to situate assistive technology design in the context of culture, in: The Proceedings of the 13th International ACM SIGACCESS Conference on Computers and Accessibility, 2011, pp. 19–26.
[21] C. Nugent, I. Cleland, L. Nugent, M.E. Estevez, A.M. Lendinez, D. Craig, F. Agnoloni, E. Tamburini, Using generative AI to assist with technology adoption assessment, in: International Conference on Ubiquitous Computing and Ambient Intelligence, Springer, 2023, pp. 202–207.
[22] X. Tong, X. Liu, X. Tan, X. Li, J. Jiang, Z. Xiong, T. Xu, H. Jiang, N. Qiao, M. Zheng, Generative models for de novo drug design, J. Med. Chem. 64 (19) (2021) 14011–14027.
[23] A.K. Tanwani, S. Calinon, A generative model for intention recognition and manipulation assistance in teleoperation, in: 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS, IEEE, 2017, pp. 43–50.
[24] W. Chi, G. Dagnino, T.M. Kwok, A. Nguyen, D. Kundrat, M.E. Abdelaziz, C. Riga, C. Bicknell, G.-Z. Yang, Collaborative robot-assisted endovascular catheterization with generative adversarial imitation learning, in: 2020 IEEE International Conference on Robotics and Automation, ICRA, IEEE, 2020, pp. 2414–2420.
[25] K. Nova, Generative AI in healthcare: advancements in electronic health records, facilitating medical languages, and personalized patient care, J. Adv. Anal. Healthc. Manag. 7 (1) (2023) 115–131.
[26] J. Yang, H. Jin, R. Tang, X. Han, Q. Feng, H. Jiang, S. Zhong, B. Yin, X. Hu, Harnessing the power of llms in practice: A survey on chatgpt and beyond, ACM Trans. Knowl. Discov. Data 18 (6) (2024) 1–32.
[27] Y. Li, M. Du, R. Song, X. Wang, Y. Wang, A survey on fairness in large language models, 2023, arXiv preprint arXiv:2308.10149.
[28] Z. Ji, N. Lee, R. Frieske, T. Yu, D. Su, Y. Xu, E. Ishii, Y.J. Bang, A. Madotto, P. Fung, Survey of hallucination in natural language generation, ACM Comput. Surv. 55 (12) (2023) 1–38.
[29] E. Cambria, L. Malandri, F. Mercorio, N. Nobani, A. Seveso, XAI meets LLMs: A survey of the relation between explainable AI and large language models, 2024, arXiv preprint arXiv:2407.15248.
[30] D. Helen, N. Suresh, Generative AI in healthcare: Opportunities, challenges, and future perspectives, Revolut. Healthc. Sec. AI (2024) 79–90.
[31] S. Sai, A. Gaur, R. Sai, V. Chamola, M. Guizani, J.J. Rodrigues, Generative ai for transformative healthcare: A comprehensive study of emerging models, applications, case studies and limitations, IEEE Access (2024).
[32] D.A. Reynolds, et al., Gaussian mixture models, in: Encyclopedia of biometrics, vol. 741, (no. 659–663) Springer, Berlin, 2009.
[33] S.R. Eddy, Hidden Markov models, Curr. Opin. Struct. Biol. 6 (3) (1996) 361–365.
[34] D.P. Kingma, M. Welling, et al., An introduction to variational autoencoders, Found. Trends Mach. Learn. 12 (4) (2019) 307–392.
[35] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, Y. Bengio, Generative adversarial networks, Commun. ACM 63 (11) (2020) 139–144.
[36] J. Ho, A. Jain, P. Abbeel, Denoising diffusion probabilistic models, Adv. Neural Inf. Process. Syst. 33 (2020) 6840–6851.
[37] S. Zhao, J. Song, S. Ermon, Infovae: Balancing learning and inference in variational autoencoders, in: Proceedings of the Aaai Conference on Artificial Intelligence, vol. 33, (no. 01) 2019, pp. 5885–5892.
[38] J. Klys, J. Snell, R. Zemel, Learning latent subspaces in variational autoencoders, Adv. Neural Inf. Process. Syst. 31 (2018).
[39] K.-L. Lim, X. Jiang, C. Yi, Deep clustering with variational autoencoder, IEEE Signal Process. Lett. 27 (2020) 231–235.
[40] Y. Pu, Z. Gan, R. Henao, X. Yuan, C. Li, A. Stevens, L. Carin, Variational autoencoder for deep learning of images, labels and captions, Adv. Neural Inf. Process. Syst. 29 (2016).
[41] A. Genevay, G. Peyré, M. Cuturi, GAN and VAE from an optimal transport point of view, 2017, arXiv preprint arXiv:1706.01807.
[42] M. Hajij, G. Zamzmi, R. Paul, L. Thukar, Normalizing flow for synthetic medical images generation, in: 2022 IEEE Healthcare Innovations and Point of Care Technologies, HI-POCT, IEEE, 2022, pp. 46–49.
[43] X. Guo, J.W. Gichoya, S. Purkayastha, I. Banerjee, CVAD: An anomaly detector for medical images based on cascade VAE, in: Workshop on Medical Image Learning with Limited and Noisy Data, Springer, 2022, pp. 187–196.
[44] I. Cetin, M. Stephens, O. Camara, M.A.G. Ballester, Attri-VAE: Attribute-based interpretable representations of medical images with variational autoencoders, Comput. Med. Imaging Graph. 104 (2023) 102158.
[45] T. Nguyen, T. Le, H. Vu, D. Phung, Dual discriminator generative adversarial nets, Adv. Neural Inf. Process. Syst. 30 (2017).
[46] C. Han, H. Hayashi, L. Rundo, R. Araki, W. Shimoda, S. Muramatsu, Y. Furukawa, G. Mauri, H. Nakayama, GAN-based synthetic brain MR image generation, in: 2018 IEEE 15th International Symposium on Biomedical Imaging, ISBI 2018, IEEE, 2018, pp. 734–738.
[47] A. Bissoto, E. Valle, S. Avila, Gan-based data augmentation and anonymization for skin-lesion analysis: A critical review, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2021, pp. 1847–1856.
[48] D. Mukherkjee, P. Saha, D. Kaplun, A. Sinitca, R. Sarkar, Brain tumor image generation using an aggregation of GAN models with style transfer, Sci. Rep. 12 (1) (2022) 9141.
[49] F. Boutros, M. Huber, P. Siebke, T. Rieber, N. Damer, SFace: Privacy-friendly and accurate face recognition using synthetic data, in: IEEE International Joint Conference on Biometrics, IJCB 2022, Abu Dhabi, United Arab Emirates, October 10-13, 2022, IEEE, 2022, pp. 1–11, http://dx.doi.org/10.1109/IJCB54206.2022.10007961.
[50] F. Boutros, M. Klemt, M. Fang, A. Kuijper, N. Damer, ExFaceGAN: Exploring identity directions in GAN's learned latent space for synthetic identity generation, in: IEEE International Joint Conference on Biometrics, IJCB 2023, Ljubljana, Slovenia, September 25-28, 2023, IEEE, 2023, pp. 1–10, http://dx.doi.org/10.1109/IJCB57857.2023.10449036.
[51] F. Boutros, M. Huber, A.T. Luu, P. Siebke, N. Damer, SFace2: Synthetic-based face recognition with w-space identity-driven sampling, IEEE Trans. Biom. Behav. Identity Sci. 6 (3) (2024) 290–303, http://dx.doi.org/10.1109/TBIOM.2024.3371502.
[52] J. Sohl-Dickstein, E. Weiss, N. Maheswaranathan, S. Ganguli, Deep unsupervised learning using nonequilibrium thermodynamics, in: International Conference on Machine Learning, PMLR, 2015, pp. 2256–2265.
[53] R. Rombach, A. Blattmann, D. Lorenz, P. Esser, B. Ommer, High-resolution image synthesis with latent diffusion models, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2022, pp. 10684–10695.
[54] N. Damer, M. Fang, P. Siebke, J.N. Kolf, M. Huber, F. Boutros, Mordiff: Recognition vulnerability and attack detectability of face morphing attacks created by diffusion autoencoders, in: 2023 11th International Workshop on Biometrics and Forensics, IWBF, IEEE, 2023, pp. 1–6.
[55] F. Boutros, J.H. Grebe, A. Kuijper, N. Damer, IDiff-face: Synthetic-based face recognition through fizzy identity-conditioned diffusion models, in: IEEE/CVF International Conference on Computer Vision, ICCV 2023, Paris, France, October 1-6, 2023, IEEE, 2023, pp. 19593–19604, http://dx.doi.org/10.1109/ICCV51070.2023.01800.
[56] A. Lugmayr, M. Danelljan, A. Romero, F. Yu, R. Timofte, L. Van Gool, Repaint: Inpainting using denoising diffusion probabilistic models, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2022, pp. 11461–11471.

[57] S. Gao, X. Liu, B. Zeng, S. Xu, Y. Li, X. Luo, J. Liu, X. Zhen, B. Zhang, Implicit diffusion models for continuous super-resolution, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2023, pp. 10021–10030.
[58] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A.N. Gomez, Ł. Kaiser, I. Polosukhin, Attention is all you need, Adv. Neural Inf. Process. Syst. 30 (2017).
[59] J. Devlin, M.-W. Chang, K. Lee, K. Toutanova, Bert: Pre-training of deep bidirectional transformers for language understanding, 2018, arXiv preprint arXiv:1810.04805.
[60] H. Touvron, T. Lavril, G. Izacard, X. Martinet, M.-A. Lachaux, T. Lacroix, B. Rozière, N. Goyal, E. Hambro, F. Azhar, et al., Llama: Open and efficient foundation language models, 2023, arXiv preprint arXiv:2302.13971.
[61] D. Zhang, Y. Yu, C. Li, J. Dong, D. Su, C. Chu, D. Yu, MM-LLMs: Recent advances in multimodal large language models, 2024, arXiv preprint arXiv:2401.13601.
[62] J. Li, D. Li, S. Savarese, S. Hoi, Blip-2: Bootstrapping language-image pre-training with frozen image encoders and large language models, in: International Conference on Machine Learning, PMLR, 2023, pp. 19730–19742.
[63] H. Liu, C. Li, Q. Wu, Y.J. Lee, Visual instruction tuning, Adv. Neural Inf. Process. Syst. 36 (2024).
[64] S. Islam, M.T. Aziz, H.R. Nabil, J.R. Jim, M.F. Mridha, M.M. Kabir, N. Asai, J. Shin, Generative adversarial networks (GANs) in medical imaging: Advancements, applications, and challenges, IEEE Access 12 (2024) 35728–35753, http://dx.doi.org/10.1109/ACCESS.2024.3370848.
[65] S. Kazeminia, C. Baur, A. Kuijper, B. van Ginneken, N. Navab, S. Albarqouni, A. Mukhopadhyay, GANs for medical image analysis, Artif. Intell. Med. 109 (2020) 101938.
[66] Y. Chen, X.-H. Yang, Z. Wei, A.A. Heidari, N. Zheng, Z. Li, H. Chen, H. Hu, Q. Zhou, Q. Guan, Generative adversarial networks in medical image augmentation: a review, Comput. Biol. Med. 144 (2022) 105382.
[67] A. You, J.K. Kim, I.H. Ryu, T.K. Yoo, Application of generative adversarial networks (GAN) for ophthalmology image domains: a survey, Eye Vis. 9 (1) (2022) 6.
[68] S. Xun, D. Li, H. Zhu, M. Chen, J. Wang, J. Li, M. Chen, B. Wu, H. Zhang, X. Chai, et al., Generative adversarial networks in medical image segmentation: A review, Comput. Biol. Med. 140 (2022) 105063.
[69] A. Padmanabha, J. Yuan, J. Gupta, Z. Karachiwalla, C. Majidi, H. Admoni, Z. Erickson, Voicepilot: Harnessing LLMs as speech interfaces for physically assistive robots, 2024, arXiv preprint arXiv:2404.04066.
[70] T. Mayer, Improving health services with conversational AI and LLMs: A look at present and future impacts, Integr. J. Sci. Technol. 1 (8) (2024).
[71] H. Qin, Generative AI applications in helping children with speech language issues, in: Proceedings of the AAAI Symposium Series, vol. 3, 2024, pp. 399–400.
[72] Y. Tang, L. Chen, Z. Chen, W. Chen, Y. Cai, Y. Du, F. Yang, L. Sun, EmoEden: Applying generative artificial intelligence to emotional learning for children with high-function autism, in: Proceedings of the CHI Conference on Human Factors in Computing Systems, 2024, pp. 1–20.
[73] A. Fiora, F. Piferi, P. Crovari, F. Garzotto, Exploring large language models for the education of individuals with cognitive impairments, in: INTED2024 Proceedings, IATED, 2024, pp. 4479–4487.
[74] S. Zhang, Y. Ma, L. Fang, H. Jia, S. D'Alfonso, V. Kostakos, Enabling on-device llms personalization with smartphone sensing, 2024, arXiv preprint arXiv:2407.04418.
[75] D. Peng, Z. Fu, J. Wang, Pocketllm: Enabling on-device fine-tuning for personalized LLMs, 2024, arXiv preprint arXiv:2407.01031.
[76] B. Yang, L. He, K. Liu, Z. Yan, Viassist: Adapting multi-modal large language models for users with visual impairments, 2024, arXiv preprint arXiv:2404.02508.
[77] A. Bala, Multimodal LLM using Federated Visual Instruction Tuning for Visually Impaired (Ph.D. thesis), Faculty of the Graduate School of the University at Buffalo, The State ..., 2024.
[78] B.R. Bryant, P.C. Seay, The technology-related assistance to individuals with disabilities act: Relevance to individuals with learning disabilities and their advocates, J. Learn. Disabil. 31 (1) (1998) 4–15.
[79] O. Korn, A. Schmidt, T. Hörz, Assistive systems in production environments: exploring motion recognition and gamification, in: Proceedings of the 5th International Conference on Pervasive Technologies Related To Assistive Environments, 2012, pp. 1–5.
[80] O. Korn, M. Funk, A. Schmidt, Assistive systems for the workplace: Towards context-aware assistance, in: Gamification: Concepts, Methodologies, Tools, and Applications, IGI Global, 2015, pp. 1936–1949.
[81] S. Qiu, P. An, K. Kang, J. Hu, T. Han, M. Rauterberg, Investigating socially assistive systems from system design and evaluation: A systematic review, Univers. Access Inf. Soc. (2023) 1–25.
[82] S. Madanian, I. Nakarada-Kordic, S. Reay, et al., Patients' perspectives on digital health tools, PEC Innov. 2 (2023) 100171.
[83] G. Revell, Generative AI applications in the health and well-being domain: Virtual and robotic assistance and the need for niche language models (NLMs), in: Applications of Generative AI, Springer, 2024, pp. 189–207.
[84] World Health Organization, Assistive technology, 2024, https://www.who.int/news-room/fact-sheets/detail/assistive-technology. (Accessed 19 September 2024).
[85] A. Tytarenko, Reducing risk for assistive reinforcement learning policies with diffusion models, 2024, arXiv preprint arXiv:2405.07603.
[86] A. Adedeji, S. Joshi, B. Doohan, The sound of healthcare: Improving medical transcription ASR accuracy with large language models, 2024, arXiv preprint arXiv:2402.07658.
[87] Y. Jiang, C. Poellabauer, A sequence-to-sequence based error correction model for medical automatic speech recognition, in: 2021 IEEE International Conference on Bioinformatics and Biomedicine, BIBM, IEEE, 2021, pp. 3029–3035.
[88] M. Jelassi, O. Jemai, J. Demongeot, Revolutionizing radiological analysis: The future of French language automatic speech recognition in healthcare, Diagnostics 14 (9) (2024) 895.
[89] S. Mondal, S. Das, V.G. Vrana, How to bell the cat? A theoretical review of generative artificial intelligence towards digital disruption in all walks of life, Technologies 11 (2) (2023) 44.
[90] M. Kuzlu, Z. Xiao, S. Sarp, F.O. Catak, N. Gurler, O. Guler, The rise of generative artificial intelligence in healthcare, in: 2023 12th Mediterranean Conference on Embedded Computing, MECO, IEEE, 2023, pp. 1–4.
[91] K. Singhal, S. Azizi, T. Tu, S.S. Mahdavi, J. Wei, H.W. Chung, N. Scales, A. Tanwani, H. Cole-Lewis, S. Pfohl, et al., Large language models encode clinical knowledge, Nature 620 (7972) (2023) 172–180.
[92] A. Chowdhery, S. Narang, J. Devlin, M. Bosma, G. Mishra, A. Roberts, P. Barham, H.W. Chung, C. Sutton, S. Gehrmann, et al., Palm: Scaling language modeling with pathways, J. Mach. Learn. Res. 24 (240) (2023) 1–113.
[93] D. Jin, E. Pan, N. Oufattole, W.-H. Weng, H. Fang, P. Szolovits, What disease does this patient have? A large-scale open domain question answering dataset from medical exams, Appl. Sci. 11 (14) (2021) 6421.
[94] A. Pal, L.K. Umapathi, M. Sankarasubbu, Medmcqa: A large-scale multi-subject multi-choice dataset for medical domain question answering, in: Conference on Health, Inference, and Learning, PMLR, 2022, pp. 248–260.
[95] Q. Jin, B. Dhingra, Z. Liu, W.W. Cohen, X. Lu, Pubmedqa: A dataset for biomedical research question answering, 2019, arXiv preprint arXiv:1909.06146.
[96] D. Hendrycks, C. Burns, S. Basart, A. Zou, M. Mazeika, D. Song, J. Steinhardt, Measuring massive multitask language understanding, 2020, arXiv preprint arXiv:2009.03300.
[97] A. Hadid, From mind-reading to health-reading machines: Towards contactless health diagnosis using generative artificial intelligence, Nafath 9 (25) (2024).
[98] P.-H. Tseng, I.G. Cameron, G. Pari, J.N. Reynolds, D.P. Munoz, L. Itti, High-throughput classification of clinical populations from natural viewing eye movements, J. Neurol. 260 (2013) 275–284.
[99] T. Langdell, Recognition of faces: An approach to the study of autism, J. Child Psychol. Psychiatr. 19 (3) (1978) 255–268.
[100] R. Sabo, Š. Beňuš, V. Kevická, M. Trnka, M. Rusko, S. Darjaa, J. Kejriwal, Towards the use of social robot furhat and generative AI in testing cognitive abilities, Human Affairs 34 (2) (2024) 224–243.
[101] L. Dieker, T. Zaugg, Artificial intelligence and the intersectionality of disability, in: The Palgrave Encyclopedia of Disability, Springer, 2024, pp. 1–8.
[102] C. Elbro, M. Dalby, S. Maarbjerg, Language-learning impairments: a 30-year follow-up of language-impaired children with and without psychiatric, neurological and cognitive difficulties, Int. J. Lang. Commun. Disord. 46 (4) (2011) 437–448.
[103] D.L. Edgar, L.I. Rosa-Lugo, The critical shortage of speech-language pathologists in the public school setting: Features of the work environment that affect recruitment and retention, 2007.
[104] Y. Lyu, P. An, H. Zhang, K. Katsuragawa, J. Zhao, Designing AI-enabled games to support social-emotional learning for children with autism spectrum disorders, 2024, arXiv preprint arXiv:2404.15576.
[105] A.K. Upadhyay, Generative AI and training employees with special needs, Strategic HR Rev. (2024).
[106] S. Fazli, S. Dähne, W. Samek, F. Bießmann, K.-R. Müller, Learning from more than one data source: data fusion techniques for sensorimotor rhythm-based brain–computer interfaces, Proc. IEEE 103 (6) (2015) 891–906.
[107] S. Eldawlatly, On the role of generative artificial intelligence in the development of brain-computer interfaces, BMC Biomed. Eng. 6 (1) (2024) 4.
[108] C.R. Victor, S.J. Scambler, S. Shah, D.G. Cook, T. Harris, E. Rink, S. De Wilde, Has loneliness amongst older people increased? An investigation into variations between cohorts, Ageing Soc. 22 (5) (2002) 585–597.
[109] G. Sundström, E. Fransson, B. Malmberg, A. Davey, Loneliness among older Europeans, Eur. J. Ageing 6 (2009) 267–275.
[110] E. Courtin, M. Knapp, Social isolation, loneliness and health in old age: a scoping review, Health Soc. Care Community 25 (3) (2017) 799–812.
[111] R. Weiss, Loneliness: The Experience of Emotional and Social Isolation, MIT Press, 1975.
[112] L. Heylen, The older, the lonelier? Risk factors for social loneliness in old age, Ageing Soc. 30 (7) (2010) 1177–1196.

[113] R.-L. Heikkinen, M. Kauppinen, Depressive symptoms in late life: a 10-year follow-up, Arch. Gerontol. Geriatrics 38 (3) (2004) 239–250.

[114] R.S. Wilson, K.R. Krueger, S.E. Arnold, J.A. Schneider, J.F. Kelly, L.L. Barnes, Y. Tang, D.A. Bennett, Loneliness and risk of Alzheimer disease, Arch. Gen. Psychiatry 64 (2) (2007) 234–240.

[115] B. Pani, J. Crawford, K.-A. Allen, Can generative artificial intelligence foster belongingness, social support, and reduce loneliness? A conceptual analysis, Appl. Gener. AI (2024) 261–276.

[116] H. Griffith, H. Rathore, Personalized aging-in-place support through fine-tuning of generative AI models, in: 2023 Eighth International Conference on Mobile and Secure Services (MobiSecServ), vol. CFP23RAC-ART, 2023, pp. 1–2, http://dx.doi.org/10.1109/MobiSecServ58080.2023.10329224.

[117] S.L. Wright, Loneliness in the Workplace, University of Canterbury. Psychology, 2005.

[118] X. Zhou, A review of researches workplace loneliness, Psychology 9 (5) (2018) 1005–1022.

[119] H. Ozcelik, S.G. Barsade, No employee an island: Workplace loneliness and job performance, Acad. Manag. J. 61 (6) (2018) 2343–2366.

[120] S. Deniz, Effect of loneliness in the workplace on employees'job performance: A Study for hospital employees, Int. J. Health Serv. Res. Policy 4 (3) (2019) 214–224.

[121] S. Zaccolo, Artificial Intelligence as a Creativity Companion, OCAD University, 2020.

[122] Z. Xie, X. Wu, Y. Xie, Can interaction with generative artificial intelligence enhance learning autonomy? A longitudinal study from comparative perspectives of virtual companionship and knowledge acquisition preferences, J. Comput. Assist. Learn. (2024).

[123] M. Wermelinger, Using github copilot to solve simple programming problems, in: Proceedings of the 54th ACM Technical Symposium on Computer Science Education V. 1, 2023, pp. 172–178.

[124] B. Puryear, G. Sprint, Github copilot in the classroom: learning to code with AI assistance, J. Comput. Sci. Colleges 38 (1) (2022) 37–47.

[125] W. Seymour, E. Rader, Speculating about multi-user conversational interfaces and LLMs: What if chatting wasn't so lonely? in: Proceedings of the 6th ACM Conference on Conversational User Interfaces, 2024, pp. 1–4.

[126] Z. Jiang, H. Lin, Y. Zhong, Q. Huang, Y. Chen, Z. Zhang, Y. Peng, X. Li, C. Xie, S. Nong, et al., {MegaScale}: Scaling large language model training to more than 10,000 {gpus}, in: 21st USENIX Symposium on Networked Systems Design and Implementation (NSDI 24), 2024, pp. 745–760.

[127] N. Jouppi, G. Kurian, S. Li, P. Ma, R. Nagarajan, L. Nai, N. Patil, S. Subramanian, A. Swing, B. Towles, et al., Tpu v4: An optically reconfigurable supercomputer for machine learning with hardware support for embeddings, in: Proceedings of the 50th Annual International Symposium on Computer Architecture, 2023, pp. 1–14.

[128] F. Zeng, W. Gan, Y. Wang, S.Y. Philip, Distributed training of large language models, in: 2023 IEEE 29th International Conference on Parallel and Distributed Systems, ICPADS, IEEE, 2023, pp. 840–847.

[129] J. Wei, Y. Tay, R. Bommasani, C. Raffel, B. Zoph, S. Borgeaud, D. Yogatama, M. Bosma, D. Zhou, D. Metzler, et al., Emergent abilities of large language models, 2022, arXiv preprint arXiv:2206.07682.

[130] X. Zhu, J. Li, Y. Liu, C. Ma, W. Wang, A survey on model compression for large language models, 2023, arXiv preprint arXiv:2308.07633.

[131] J. Achiam, S. Adler, S. Agarwal, L. Ahmad, I. Akkaya, F.L. Aleman, D. Almeida, J. Altenschmidt, S. Altman, S. Anadkat, et al., Gpt-4 technical report, 2023, arXiv preprint arXiv:2303.08774.

[132] S. Montagna, S. Ferretti, L.C. Klopfenstein, A. Florio, M.F. Pengo, Data decentralisation of LLM-based chatbot systems in chronic disease self-management, in: Proceedings of the 2023 ACM Conference on Information Technology for Social Good, 2023, pp. 205–212.

[133] A. Biswas, W. Talukdar, Intelligent clinical documentation: Harnessing generative AI for patient-centric clinical note generation, 2024, arXiv preprint arXiv:2405.18346.

[134] Z. Xu, H. Xu, Z. Lu, Y. Zhao, R. Zhu, Y. Wang, M. Dong, Y. Chang, Q. Lv, R.P. Dick, et al., Can large language models be good companions? An LLM-based eyewear system with conversational common ground, Proc. ACM Interact., Mob., Wearable Ubiquitous Technol. 8 (2) (2024) 1–41.

[135] A. Radford, J.W. Kim, T. Xu, G. Brockman, C. McLeavey, I. Sutskever, Robust speech recognition via large-scale weak supervision, in: International Conference on Machine Learning, PMLR, 2023, pp. 28492–28518.

[136] A. Radford, J.W. Kim, C. Hallacy, A. Ramesh, G. Goh, S. Agarwal, G. Sastry, A. Askell, P. Mishkin, J. Clark, et al., Learning transferable visual models from natural language supervision, in: International Conference on Machine Learning, PMLR, 2021, pp. 8748–8763.

[137] K. He, X. Zhang, S. Ren, J. Sun, Identity mappings in deep residual networks, in: Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, the Netherlands, October 11–14, 2016, Proceedings, Part IV 14, Springer, 2016, pp. 630–645.

[138] Z. Wang, J. Yu, A.W. Yu, Z. Dai, Y. Tsvetkov, Y. Cao, Simvlm: Simple visual language model pretraining with weak supervision, 2021, arXiv preprint arXiv:2108.10904.

[139] B. Li, X. Qi, T. Lukasiewicz, P. Torr, Controllable text-to-image generation, Adv. Neural Inf. Process. Syst. 32 (2019).

[140] A. Ramesh, M. Pavlov, G. Goh, S. Gray, C. Voss, A. Radford, M. Chen, I. Sutskever, Zero-shot text-to-image generation, in: International Conference on Machine Learning, Pmlr, 2021, pp. 8821–8831.

[141] T. Qiao, J. Zhang, D. Xu, D. Tao, Mirrorgan: Learning text-to-image generation by redescription, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019, pp. 1505–1514.

[142] U. Singer, A. Polyak, T. Hayes, X. Yin, J. An, S. Zhang, Q. Hu, H. Yang, O. Ashual, O. Gafni, et al., Make-a-video: Text-to-video generation without text-video data, 2022, arXiv preprint arXiv:2209.14792.

[143] J.Z. Wu, Y. Ge, X. Wang, S.W. Lei, Y. Gu, Y. Shi, W. Hsu, Y. Shan, X. Qie, M.Z. Shou, Tune-a-video: One-shot tuning of image diffusion models for text-to-video generation, in: Proceedings of the IEEE/CVF International Conference on Computer Vision, 2023, pp. 7623–7633.

[144] Y. Du, S. Yang, B. Dai, H. Dai, O. Nachum, J. Tenenbaum, D. Schuurmans, P. Abbeel, Learning universal policies via text-guided video generation, Adv. Neural Inf. Process. Syst. 36 (2024).

[145] J. Merullo, L. Castricato, C. Eickhoff, E. Pavlick, Linearly mapping from image to text space, 2022, arXiv preprint arXiv:2209.15162.

[146] Y. Li, M. Min, D. Shen, D. Carlson, L. Carin, Video generation from text, in: Proceedings of the AAAI Conference on Artificial Intelligence, vol. 32, (no. 1) 2018.

[147] D. Yang, J. Yu, H. Wang, W. Wang, C. Weng, Y. Zou, D. Yu, Diffsound: Discrete diffusion model for text-to-sound generation, IEEE/ACM Trans. Audio, Speech, Lang. Process. 31 (2023) 1720–1733.

[148] M. Ebers, V.R. Hoch, F. Rosenkranz, H. Ruschemeier, B. Steinrötter, The European Commission's proposal for an artificial intelligence act—a critical assessment by members of the robotics and AI Law Society (RAILS), J 4 (4) (2021) 589–603.

[149] P. Unesco, Reimagining Our Futures Together: A New Social Contract for Education, Educational and Cultural Organization of the United Nations Paris, France, 2021.

[150] C. UNESCO, Recommendation on the ethics of artificial intelligence, 2021.

[151] W. Holmes, F. Miao, et al., Guidance for Generative AI in Education and Research, UNESCO Publishing, 2023.

[152] E. Gibney, What the EU's tough AI law means for research and ChatGPT, Nature (2024).

[153] W.-L. Chiang, L. Zheng, Y. Sheng, A.N. Angelopoulos, T. Li, D. Li, H. Zhang, B. Zhu, M. Jordan, J.E. Gonzalez, et al., Chatbot arena: An open platform for evaluating llms by human preference, 2024, arXiv preprint arXiv:2403.04132.

[154] M. Chen, J. Tworek, H. Jun, Q. Yuan, H.P.d. Pinto, J. Kaplan, H. Edwards, Y. Burda, N. Joseph, G. Brockman, et al., Evaluating large language models trained on code, 2021, arXiv preprint arXiv:2107.03374.

[155] R. Bommasani, P. Liang, T. Lee, Holistic evaluation of language models, Ann. New York Acad. Sci. 1525 (1) (2023) 140–146.

[156] J.A. Omiye, H. Gui, S.J. Rezaei, J. Zou, R. Daneshjou, Large language models in medicine: the potentials and pitfalls: a narrative review, Ann. Intern. Med. 177 (2) (2024) 210–220.

[157] N.H. Shah, D. Entwistle, M.A. Pfeffer, Creation and adoption of large language models in medicine, Jama 330 (9) (2023) 866–869.

[158] M. Karabacak, K. Margetis, Embracing large language models for medical applications: opportunities and challenges, Cureus 15 (5) (2023).

[159] F. Motoki, V. Pinho Neto, V. Rodrigues, More human than human: measuring ChatGPT political bias, Public Choice 198 (1) (2024) 3–23.

[160] D. Huang, Q. Bu, J. Zhang, X. Xie, J. Chen, H. Cui, Bias assessment and mitigation in llm-based code generation, 2023, arXiv preprint arXiv:2309.14345.

[161] L. Lucy, D. Bamman, Gender and representation bias in GPT-3 generated stories, in: Proceedings of the Third Workshop on Narrative Understanding, 2021, pp. 48–55.

[162] M. Turpin, J. Michael, E. Perez, S. Bowman, Language models don't always say what they think: Unfaithful explanations in chain-of-thought prompting, in: A. Oh, T. Naumann, A. Globerson, K. Saenko, M. Hardt, S. Levine (Eds.), in: Advances in Neural Information Processing Systems, vol. 36, Curran Associates, Inc., 2023, pp. 74952–74965.

[163] T. Räuker, A. Ho, S. Casper, D. Hadfield-Menell, Toward transparent ai: A survey on interpreting the inner structures of deep neural networks, in: 2023 Ieee Conference on Secure and Trustworthy Machine Learning, Satml, IEEE, 2023, pp. 464–483.

[164] K. Tirumala, D. Simig, A. Aghajanyan, A. Morcos, D4: Improving llm pretraining via document de-duplication and diversification, Adv. Neural Inf. Process. Syst. 36 (2024).

[165] T. Silver, V. Hariprasad, R.S. Shuttleworth, N. Kumar, T. Lozano-Pérez, L.P. Kaelbling, PDDL planning with pretrained large language models, in: NeurIPS 2022 Foundation Models for Decision Making Workshop, 2022.

[166] Z. Zhang, H. Li, Z. Zhang, Y. Qin, X. Wang, W. Zhu, Graph meets llms: Towards large graph models, in: NeurIPS 2023 Workshop: New Frontiers in Graph Learning, 2023.

[167] A. Saparov, H. He, Language models are greedy reasoners: A systematic formal analysis of chain-of-thought, 2022, arXiv preprint arXiv:2210.01240.
[168] X. Zhang, C. Du, T. Pang, Q. Liu, W. Gao, M. Lin, Chain of preference optimization: Improving chain-of-thought reasoning in LLMs, 2024, arXiv preprint arXiv:2406.09136.
[169] C. Cohn, N. Hutchins, T. Le, G. Biswas, A chain-of-thought prompting approach with llms for evaluating students' formative assessment responses in science, in: Proceedings of the AAAI Conference on Artificial Intelligence, vol. 38, (no. 21) 2024, pp. 23182–23190.
[170] F. Mercorio, M. Mezzanzanica, A. Seveso, eXDiL: A tool for classifying and explaining hospital discharge letters, in: International Cross-Domain Conference for Machine Learning and Knowledge Extraction, Springer, 2020, pp. 159–172.
[171] N. Gozzi, L. Malandri, F. Mercorio, A. Pedrocchi, XAI for myo-controlled prosthesis: Explaining EMG data for hand gesture classification, Knowl.-Based Syst. 240 (2022) 108053.
[172] J. Gribbin, M. Gribbin, Richard Feynman: A Life in Science, Icon Books, 2018.
[173] P. West, X. Lu, N. Dziri, F. Brahman, L. Li, J.D. Hwang, L. Jiang, J. Fisher, A. Ravichander, K. Chandu, et al., The generative AI paradox:"what it can create, it may not understand", in: The Twelfth International Conference on Learning Representations, 2023.
[174] A.M. Dakhel, V. Majdinasab, A. Nikanjam, F. Khomh, M.C. Desmarais, Z.M.J. Jiang, Github copilot ai pair programmer: Asset or liability? J. Syst. Softw. 203 (2023) 111734.
[175] J.-Y. Yao, K.-P. Ning, Z.-H. Liu, M.-N. Ning, L. Yuan, Llm lies: Hallucinations are not bugs, but features as adversarial examples, 2023, arXiv preprint arXiv:2310.01469.
[176] P. Manakul, A. Liusie, M.J. Gales, Selfcheckgpt: Zero-resource black-box hallucination detection for generative large language models, 2023, arXiv preprint arXiv:2303.08896.
[177] N. McKenna, T. Li, L. Cheng, M.J. Hosseini, M. Johnson, M. Steedman, Sources of hallucination by large language models on inference tasks, 2023, arXiv preprint arXiv:2305.14552.
[178] H. Quay-de la Vallee, M. Dwyer, et al., CDT-students' use of generative AI: The threat of hallucinations, 2023.
[179] S. Tonmoy, S. Zaman, V. Jain, A. Rani, V. Rawte, A. Chadha, A. Das, A comprehensive survey of hallucination mitigation techniques in large language models, 2024, arXiv preprint arXiv:2401.01313.
[180] X. Wu, R. Duan, J. Ni, Unveiling security, privacy, and ethical concerns of ChatGPT, J. Inf. Intell. 2 (2) (2024) 102–115.
[181] B.C. Das, M.H. Amini, Y. Wu, Security and privacy challenges of large language models: A survey, 2024, arXiv preprint arXiv:2402.00888.
[182] A. Golda, K. Mekonen, A. Pandey, A. Singh, V. Hassija, V. Chamola, B. Sikdar, Privacy and security concerns in generative AI: A comprehensive survey, IEEE Access (2024).
[183] T. Wang, Y. Zhang, S. Qi, R. Zhao, Z. Xia, J. Weng, Security and privacy on generative data in aigc: A survey, 2023, arXiv preprint arXiv:2309.09435.
[184] V. Iaia, To be, or not to be… original under copyright law, that is (one of) the main questions concerning AI-produced works, GRUR Int. 71 (9) (2022) 793–812.
[185] M.A. Lemley, How generative AI turns copyright law on its head, 2023, Available at SSRN 4517702.
[186] Yonah Welker, world economic forum, Generative AI holds great potential for those with disabilities - but it needs policy to shape it, 2023, https://www.weforum.org/agenda/2023/11/generative-ai-holds-potential-disabilities/. (Accessed 29 July 2024).
[187] D. Gursoy, O.H. Chi, L. Lu, R. Nunkoo, Consumers acceptance of artificially intelligent (AI) device use in service delivery, Int. J. Inf. Manage. 49 (2019) 157–169.
[188] X. Ma, Y. Huo, Are users willing to embrace ChatGPT? Exploring the factors on the acceptance of chatbots from the perspective of AIDUA framework, Technol. Soc. 75 (2023) 102362, http://dx.doi.org/10.1016/j.techsoc.2023.102362, URL https://www.sciencedirect.com/science/article/pii/S0160791X23001677.
[189] S. Feuerriegel, J. Hartmann, C. Janiesch, P. Zschech, Generative ai, Bus. Inf. Syst. Eng. 66 (1) (2024) 111–126.
[190] Accountability Act, Health insurance portability and accountability act of 1996, Public law 104 (1996) 191.
[191] P. Lewis, E. Perez, A. Piktus, F. Petroni, V. Karpukhin, N. Goyal, H. Küttler, M. Lewis, W.-t. Yih, T. Rocktäschel, et al., Retrieval-augmented generation for knowledge-intensive nlp tasks, Adv. Neural Inf. Process. Syst. 33 (2020) 9459–9474.
[192] G. Team, T. Mesnard, C. Hardin, R. Dadashi, S. Bhupatiraju, S. Pathak, L. Sifre, M. Rivière, M.S. Kale, J. Love, et al., Gemma: Open models based on gemini research and technology, 2024, arXiv preprint arXiv:2403.08295.
[193] L. Zhang, A. Rao, M. Agrawala, Adding conditional control to text-to-image diffusion models, in: IEEE/CVF International Conference on Computer Vision, ICCV 2023, Paris, France, October 1-6, 2023, IEEE, 2023, pp. 3813–3824, http://dx.doi.org/10.1109/ICCV51070.2023.00355.