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REVIEW

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ChatGPT and human-robot interaction with social assistance towards the world of AI

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ABSTRACT

ChatGPT, an advanced language model, presents an opportunity to enhance human-robot collaboration by integrating a custom voice assistant. This approach tackles a fundamental problem in human-robot interaction (HRI) effective communication between humans and machines. By combining ChatGPT's natural language processing capabilities with a tailored voice interface, users can communicate with robots in their native language. The solution involves training ChatGPT on multilingual datasets, optimizing responses for context-relevant interactions, and ensuring flexibility across robotic platforms. Compared to traditional HRI methods, ChatGPT-based voice assistants offer several advantages. They enable more natural and intuitive communication, reducing the cognitive load on users. Additionally, the language model's contextual understanding and adaptive learning capabilities facilitate more personalized and engaging interactions. However, challenges persist, including potential biases inherited from training data, difficulty handling ambiguous queries, and ensuring factual accuracy. This paper reviews the applications of ChatGPT in HRI, highlighting its potential to revolutionize human-machine collaboration. It discusses the implementation approach, advantages, and limitations. Furthermore, it explores the role of natural language processing in affective computing and emotion recognition for enhanced social intelligence in robots. Overall, the integration of ChatGPT presents a promising avenue for advancing HRI towards more seamless, productive, and user-friendly interactions.

KEYWORDS

ChatGPT; Application programming interface; Human-Robot interaction; Natural language processing

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Introduction

The development of ChatGPT represents a significant advance in conversational AI, resulting from developments in deep learning models for natural language processing (NLP). Driven by the goal of developing more complex language models, ChatGPT is designed to comprehend and produce writing that resembles that of a human. It is an extension of OpenAI's GPT architecture. ChatGPT is an excellent tool for understanding context and providing pertinent responses because it is driven by transformer-based artificial neural networks with self-awareness processes and has been trained on large datasets. Chatbot technology has been transformed by its ability to capture semantic nuances and understand conversational context, allowing for effortless interactions between humans and machines. With uses for customer service, content creation, and language translation, ChatGPT has developed into a vital tool that has advanced conversational AI systems enormously.

ChatGPT uses NLP and machine learning (ML) techniques to understand and respond to a wide variety of user inputs in a conversational way, in contrast to traditional Human-Computer Interaction (HCI) [1]. The architecture of the model, which is indicated by the title "ChatGPT," blends the Generic Pretrained Transformer (GPT) architecture with an emphasis on text production and discussion. Originally created for natural language translation, transformers have developed into a well-known class of deep learning models for a range of NLP applications. By using attention methods, they can handle issues like long-term dependencies in sequence data [2].

Machine interpretation and response to human commands have changed dramatically as a result of the combination of ML and (LLM) in HRI. Despite current ethical issues, this synergy improves robots' comprehension of natural language patterns and their capacity to work together productively in industries such as manufacturing, healthcare, education, and personal assistance. This holds out the promise of a more adaptable and efficient robotic workforce [1]. Robotics systems require a deep comprehension of real-world physics, the ability to perform physical actions, and contextual knowledge, in contrast to text-only applications. Robust commonsense knowledge, an advanced world model, and the ability to understand and carry out orders in a fashion that is both physically possible and makes sense in the real world are all necessary for generative robotics models. Token embedding models for language have been the main tool utilized in recent attempts to incorporate language into robotics systems [3]. Innovative tools are provided by social robotics, which studies human-robot interaction with an emphasis on social and emotional aspects.

1. Social engagement, in which robots generate an appropriate environment for social skills training.
2. Supporting effective expression through communication.
3. Emotional regulation, identifying and reacting to emotional cues.
4. Personalized learning, adjusting interactions based on individual needs through machine learning.

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5. Encouraging social initiations through interaction.
6. Applying robot-learned skills to social contexts in the real world.

Social robots can improve assistance, but it cannot take the place of human interactions in an inclusive approach. With the capacity to apply acquired abilities to real-world situations, the Pepper robotic system and OpenAI technology are intended to be integrated in a way that maximizes their potential for effective modified interactions [4].

Methodology

The keywords for the review used were ChatGPT, Natural Language Processing, Machine Learning, Artificial Intelligence in assistive bots, ChatGPTt in Robots for HRI collected from various sources like IEE, OpenAI, arXiv. These keywords are often searched on Google Scholar. The paper used for references was taken from the year 2000 at the least and the majority of the paper is from the recent 10 years since the development of ChatGPT. Artificial Intelligence (AI) has become increasingly prevalent in project management, offering new ways to optimize processes and enhance overall project performance. The use of AI in project management can be categorized into three main areas:

Automation

AI can automate routine tasks, such as data entry, report generation, and scheduling, allowing project managers to focus on higher-level decision-making and strategy [5].

Analytics

AI-powered analytics tools can process vast amounts of data to uncover patterns, trends, and insights that would be difficult or impossible for humans to detect manually [5].

Assistance

AI assistants, like ChatGPT-4, can provide support in various aspects of project management, from generating progress reports to facilitating communication among team members [5].

ChatGPT as a Language Model

ChatGPT, developed by OpenAI, is a sophisticated language model based on the Generative Pre-trained Transformer (GPT) architecture. Its design enables the generation of human-like text, making it a key tool in fields such as customer service, content creation, and human-robot interaction (HRI). ChatGPT's strength lies in its ability to understand and generate contextually relevant responses, facilitating natural and seamless communication between humans and machines. As a LLM, it combines deep learning and NLP techniques to create coherent and meaningful dialogues, making it invaluable for applications where human-like interaction is essential.

Key concepts and components

Attention mechanism: This feature allows neural networks to focus on specific elements of incoming data, ensuring that the most relevant information is emphasized in the model's response. This improves response accuracy by concentrating on important contextual details.

Chatbot interference: ChatGPT functions as chatbot software, mimicking human-user communication. It responds in a way that resembles real human conversations, which is essential for applications in customer service and interactive systems.

Generative model: Unlike models that only categorize or predict, ChatGPT is a generative model, meaning it creates new data, such as sentences or dialogues, based on the input it receives. This allows it to produce creative, diverse, and relevant content.

Generative Pre-trained transformer (GPT): The GPT architecture relies on training the model using both supervised and unsupervised methods, allowing it to understand and produce language similar to that of humans. The model processes vast amounts of text data to learn patterns, context, and linguistic structures.

Language model: ChatGPT is a language model that produces human-like writing. It generates text by predicting the next word in a sequence based on the previous context, resulting in fluent, natural-sounding responses [6,7].

Multimodal neurons: These neural components can interpret data across multiple formats—text, voice, and images—enabling ChatGPT and similar models to interact with diverse types of input and output.

Natural language processing (NLP): NLP is the core of ChatGPT's operation, enabling the model to analyze, understand, and generate human language. It uses algorithms to interpret text and respond accurately to queries.

Neural network: A network of interconnected nodes, or neurons, that are trained to carry out specific tasks. In ChatGPT, these neural networks form the backbone of its ability to generate language and learn from interactions.

Recent advancements in HRI, largely fueled by sophisticated models like ChatGPT, have enabled robots to collaborate with humans in more natural ways. Examples include the use of quadruped and wheeled robots in warehouses and hospitals, where they autonomously navigate and adapt to dynamic environments, reducing human workloads and improving efficiency. Collaborative robots like Baxter are also utilized for tasks such as object manipulation. Inspired by generative models like GPT, a framework named RobotGPT has been developed to create various forms of robot intelligence. While ChatGPT provides a robust foundation for robot intelligence, the launch of GPT-4 in 2023 has introduced enhanced features like improved image understanding and more accurate responses, further expanding the capabilities of robots in intelligent interactions [1,8].

Comparison of ChatGPT with Gemini and Other Large Language Models (LLM)

There are various factors that influence the quality of responses in LLMs. A comparison between ChatGPT and Google's Gemini highlights several notable differences:

Data storage: Gemini is regularly updated with the latest information, allowing it to provide real-time responses. In contrast, ChatGPT's knowledge is static, capped at September 2021 for now. This means that any developments after this time will not be reflected in ChatGPT's responses [9,10].

Search capabilities: Gemini has the ability to perform real-time searches across the internet, which enables it to access more up-to-date and diverse information. ChatGPT, on the other

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hand, is not connected to real-time data sources and instead relies on its pre-existing knowledge and training, which limits its search scope.

Biases and accuracy: While both models are susceptible to biases due to the data on which they were trained, Gemini is designed to address some of these shortcomings by leveraging newer datasets. ChatGPT, though powerful, may occasionally present information that contains biases or factual inaccuracies, as it cannot verify information in real time.

Information detail: In general, Gemini tends to provide more detailed and up-to-date information compared to ChatGPT, due to its constant internet access and newer datasets. ChatGPT excels in generating comprehensive responses but may miss critical recent developments.

Accessibility: Gemini is designed for a broad range of users, including children, and provides simplified, user-friendly responses. ChatGPT is also highly accessible but tends to offer more text-based and technical responses tailored to more mature audiences.

Underlying technology: ChatGPT is based on the GPT architecture, which emphasizes NLP capabilities, including generating contextually rich and accurate text. Gemini, while also designed for conversational agents, focuses more on handling dynamic, real-time queries through advanced data processing systems [9,11].

Contextual understanding: ChatGPT demonstrates a broader ability to understand and generate context across a variety of scenarios, offering rich textual outputs in numerous contexts. While Gemini excels in conversational queries, ChatGPT often outperforms in situations requiring deeper, more intricate textual context.

Reaction speed: Gemini offers faster, more immediate responses, especially when dealing with real-time events or internet-connected queries. ChatGPT, while efficient, operates at a slower pace in such cases due to its lack of real-time connectivity.

Model parameters: ChatGPT contains 175 billion parameters, giving it immense capability in generating diverse text and maintaining context. In comparison, Gemini utilizes a different parameter structure with fewer parameters (1.37 billion), but compensates with a vast vocabulary, over 1.5 trillion words.

Plagiarism checking: ChatGPT includes a plagiarism-checking capability, which makes it useful for academic and content creation applications. Gemini currently lacks this function, limiting its utility in certain formal writing and content creation tasks.

Customer interaction: ChatGPT excels in customer interactions, particularly in FAQ responses and problem-solving due to its extensive NLP capabilities. Gemini, while effective in conversational responses, may not handle complex customer queries with the same level of nuance.

Both ChatGPT and Gemini present unique strengths and limitations. Gemini's real-time access and simplified interaction suit users looking for fast, up-to-date answers, but it sometimes provides unreliable sources or robotic-sounding responses. ChatGPT, in contrast, is superior in generating complex, well-rounded text, making it ideal for collaboration, text generation, and more nuanced queries, though it lacks real-time updates and picture-sharing capabilities. Together, these models demonstrate the diverse approaches to conversational AI in modern generative systems (Figure 1) [12,13].

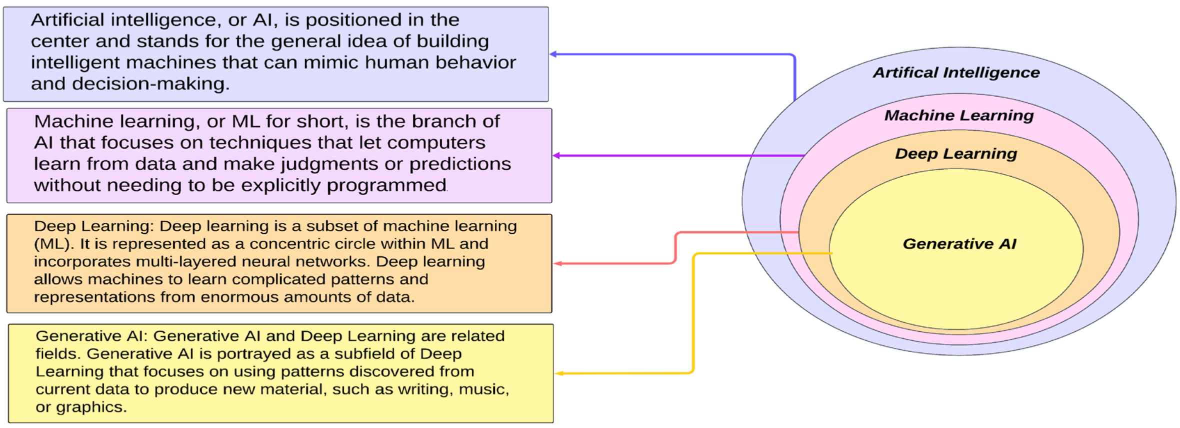

Figure 1. Comparative Model of AI, ML, Deep Learning and Generative AI.

Advantages and Limitations of ChatGPT

Implementing OpenAI's ChatGPT AI model into self-governing systems offers an innovative method to improve human-robot communication and decision-making processes. By utilizing ChatGPT's contextual knowledge, dynamic adaptability, and strong reasoning powers, robots may interpret user inquiries, adjust to real-time facts, and carry out comprehensive analysis for well-informed decision-making [14]. The system prioritizes human-like interaction, which promotes trust and eases user-to-user communication. A data flow graphic embedded in the text highlights the adaptability and ongoing learning of the system and discusses ChatGPT's handling of linguistic ambiguity and complexity, which is essential for comprehending complex user instructions. The study highlights ChatGPT's benefits in answering complex inquiries, assisting with coding, creating visuals, creating music, and offering medical assistance, despite downsides such as infrequent nonsense creation, sensitivity to word choice, and limitations in post-2021 event interpretation [15].

The quality of training data is another challenge faced by generative AI. The quality of generative AI models largely depends on the quality of the training data. Any factual errors,

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unbalanced information sources, or biases embedded in the training data may be reflected in the output of the model [16]. As shown in Tables 1a and 1b generalizes the Advantages and Disadvantages. ChatGPT has several limitations, including inherent biases in its training data, incomplete or outdated knowledge, and difficulty discerning factual accuracy. OpenAI's ChatGPT is no doubt a breakthrough for the HRI Innovations. However, these limitations cannot be avoided, and build a proper strategy to overcome or bypass them.

Table 1a. Advantages with ChatGPT.

Advantages	Details	References
Corrective Capability	Users can correct ChatGPT if its response contains inaccuracies or misleading information.	[17,18]
Explanatory Ability	ChatGPT can provide detailed explanations based on its responses.	[17,18]
Enhanced Context Understanding	It can comprehend and respond to complex inputs, making it more effective in generating relevant text.	[19,20]
Reduced Biases	Efforts are ongoing to minimize biases in training data, leading to more objective and balanced outputs.	[19,20]
Fine-Tuning Capabilities	ChatGPT can be fine-tuned for specific tasks, catering to the unique needs of researchers in various disciplines.	[19,20]

Table 1b. Challenges with ChatGPT.

Disadvantages	Details	References
Inaccurate or Misleading Information	ChatGPT's responses may contain inaccuracies, as it relies on patterns learned from training data rather than deep understanding.	[16,19,21]
Hallucination	The content generated may sometimes be nonsensical, incorrect, or contain factual errors.	[16]
Knowledge Limitation	Its knowledge is limited to the training data with a cutoff in 2021, making it unable to provide real-time updates or verify new developments.	[9,16,19]
Quality of Training Data	It can be difficult to ensure the quality of datasets required for generative AI.	[16,19,20]
Handling Ambiguous Queries	ChatGPT may struggle with ambiguous questions, generating plausible-sounding but irrelevant responses.	[19,20]
Potential Harm	It might provide harmful medical advice, generate fake accounts, create online scams, and threaten intellectual development and clerical jobs.	[16,21]

HRI with NLP System Design

The field of HRI is currently going through an abrupt transformation as a result of the adoption of artificial intelligence (AI), which has the potential to greatly expand robot capabilities. Through the use of advanced characteristics like machine learning, logical reasoning, and natural language processing, AI enables robots to interact with humans more naturally and responsively. This progress might lead to more seamless interactions with robots across a range of fields, therefore simplifying our lives. Figure 2 shows a workflow ChatGPT-based robot where speech-to-text and text-to-speech along with GPT is integrated with a robot.

By considering the contextual information and evaluating the ambiguity of information, GPT3.5 generates natural responses to either further clarify the information with the human operators via conversations or control the robot. When communicating with human operators, the ChatGPT Robot AI assistant generates prompts, presents the prompts to human operators, and waits for further instructions [22].

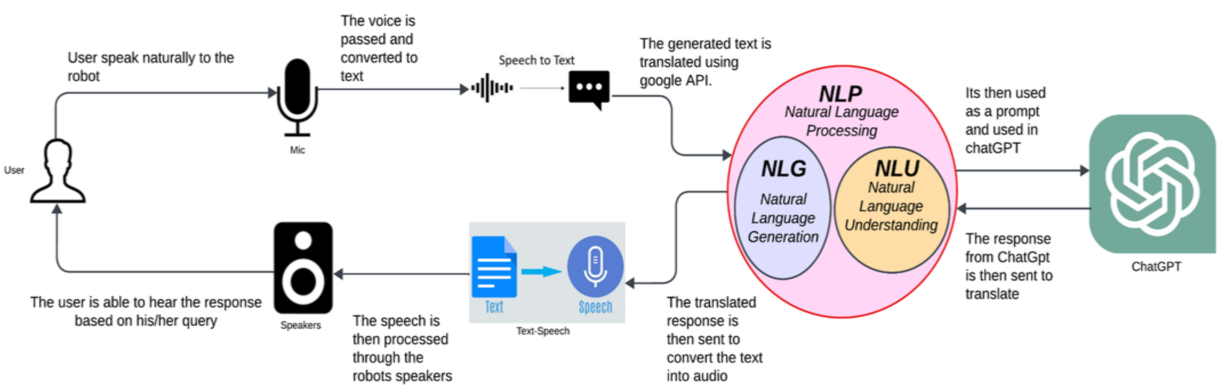

Figure 2. System workflow of ChatGPT-based robot.

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Robot and human communication may take many different forms, and the type of communication that occurs greatly depends on the proximity the robot and human are to one another. As a result, there are two primary categories of interaction or communication:

1. **Proximate interaction:** This happens when people and robots are physically near to one another.
2. **Remote interaction:** In this case, humans and robots are geographically or temporally apart.

These proximity-based categories make it possible to distinguish between apps that need to be mobile, flexible physically, or sociable. Fundamentally, distinguishing between local and remote contact assists in determining the particular requirements and features of many scenarios involving human-robot communication [23,24].

The information exchange between humans and robots is achieved by interactions with the environment as shown in figure 3 depending on which side the arbitration leans towards humans or robots [25]. As these applications imply, some forms of human-robot interaction involve direct physical contact often referred to as physical human-robot interaction (pHRI). While much of the literature related to pHRI has traditionally had a strong focus on ensuring safety during the interaction between humans and robots [26].

The nuances that define our peers' voices and facial expressions during casual talks act as windows into their emotional states, exposing the underlying feelings linked to physiological changes in the larynx and vocal folds. Robots' comprehension of human speech and emotions is critical in the field of HRI. It uses automatic acoustic emotion recognition (AER), avoiding semantic considerations in favor of grammar, voice quality, and spectral data. For the purpose of feature extraction and classification in AER, traditional machine learning techniques such as support vector machines, Gaussian mixture models, and hidden Markov models have been applied. However, more recently, deep learning techniques such as convolutional neural networks, recurrent neural networks, deep belief networks, and deep Boltzmann machines have shown to be more successful, indicating an improvement toward thorough emotion identification [27,28].

While the traditional focus of HRI research has been on the physical interactions between people and robots, with an emphasis on industrial robots, social intelligence which is represented by qualities like empathy has come into its own. A social robot needs to demonstrate its agency capability, use gestures, gaze in the right places, and behave in the right spaces in order to effectively communicate empathy. Together, these components improve the experience of human-robot contact in a way that goes beyond just the tangible [29]. Semantic comprehension problems in the context of social robots are accomplished by means of feature extraction, which tackles issues like gender detection, age estimation, speaker localization, voice recognition, and speech-based perceptual semantics. These jobs entail deciphering spoken conversations and extracting pertinent information, allowing social robots to communicate more effectively based on various voice-related characteristics [23]. It is critical to design an assistive, intuitive social robot that will improve autonomy and quality of life for senior citizens suffering from cognitive disorders such as Alzheimer's [30].

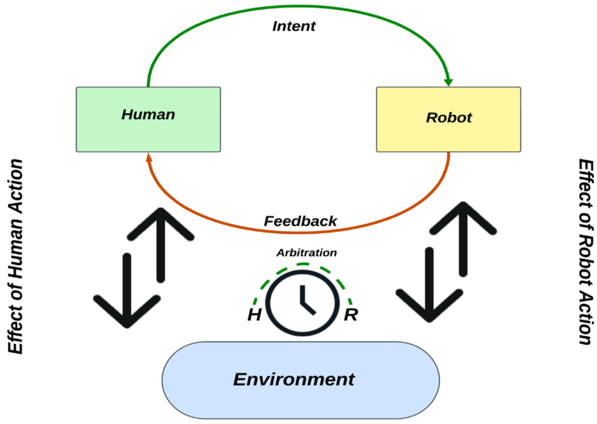

Figure 3. Information Exchange of ChatGPT-based Robot.

Physical Human Interaction

Building a solid partnership is essential in the field of HRI if robots are to perform as fully functional members of a team, particularly under pressure. It becomes clear that trust is a crucial component that affects decision-making, acceptance of information, and system performance as a whole. The study highlights how robot attributes, especially performance, affect the formation of trust, highlighting the necessity of taking these aspects into account when designing and training human-robot interaction systems [31]. Likewise, the difficulties in guaranteeing safe physical HRI are examined, highlighting metrics related to dependability and safety. Strict analysis of collision risks and possible injuries during human-robot interaction clarifies safety requirements and severity indices. The thorough investigation seeks to provide a solid basis for the safe incorporation of robots into a variety of human environments [32,33].

Analyzing the industrial, professional service, and personal service sectors of robots reveals different applications and degrees of autonomy. The transition to service robots poses new difficulties for human-robot interaction, bringing up issues with interfaces and communication strategies for a range of interactions. The study highlights unanswered concerns about the influence of physical appearance, interface scalability, autonomy's function, and the direction that human-robot interaction will take in emerging applications [34]. On top of that, the utilization of industrial robotics in the oil and gas sector underscores the necessity for enhanced automation in demanding conditions. Particularly in cases involving robot collaboration or the replacement of human operators, trust, accountability, and organizational integration are all factors [35].

Looking into how humans perceive a robot's physical versus virtual presence during cooperative tasks shows how vital physical presence is in fostering engagement, trust, and respect. Researchers found that subjects were more likely to follow instructions and provide a physically present robot more personal space, which emphasizes the need of taking presence as a factor when creating successful human-robot interactions [36,37]. For urban search and rescue operations, challenges in rescue robots include minimizing the human-to-robot ratio, resolving communication problems, and guaranteeing acceptance within social structures. The analysis emphasizes how critical it is for people to evaluate sensor data and make crucial

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decisions during high-stress missions, which is why it matters that robots and communication technology advance [38].

Even though it faces difficulties such as precisely measuring preferences, a behavior adaptation system for robots in human-robot interactions uses policy gradient reinforcement learning (PGRL) to modify important parameters based on human comfort signals, demonstrating encouraging results in a pilot study with a humanoid robot [39]. A different experiment assesses how an innovative robot affects human observers, emphasizing the role that gaze control plays in improving interaction experiences and pinpointing important elements such as comfort and enjoyment in human perceptions of the robot [40]. Humans and robots can communicate using a variety of approaches, which raises concerns regarding interface design, the significance of physical appearance, the scalability of these methods to group settings, the relevance of autonomy, and the potential evolution of human-robot interaction in upcoming applications [34]. The three main kinds of robots, their difficulties in interacting with humans, and the results of the analysis along with related open questions are shown in this block diagram in Figure 4.

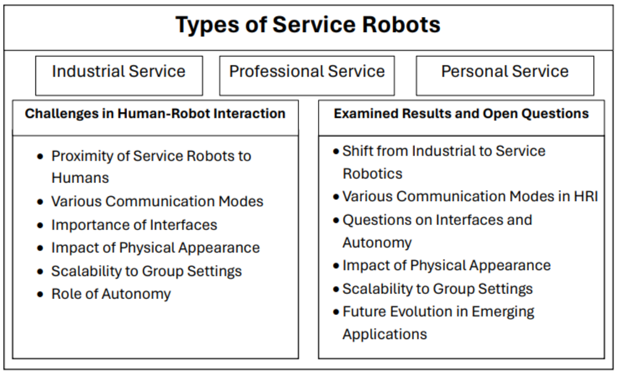

Figure 4. The block diagram three major categories of robots.

Subsequently, a study that divides 42 measures into three categories human, robot, and system reveals issues with precisely evaluating features. The measurements ignore the particular issues faced by remote presence applications in favor of taskable agents and social domains [41]. A further assessment examines the current state of social gaze in HRI and divides research into three categories: technology, design, and human centers. The importance of physical appearance in gaze capabilities and costs is addressed, along with a discussion of many sorts of gazes and their interpretations. Physical gaze functions, micro vs macro-scale reactions, and the integration of gaze with other social behaviors in HRI are among the unanswered questions [42].

As robots become more autonomous, it distinguishes HRI from traditional human-computer interaction, considering factors like dynamic control systems, autonomy, and real-world environments. Five interaction roles (supervisor, operator, teammate, bystander, and mechanic) with specific tasks and awareness needs, It discusses aspects of mobile robots, such as their physical nature, dynamic behavior, environmental challenges, and autonomy. The key focus is on collaborative control, situational awareness evaluation, and a multidisciplinary approach to successful HRI, covering both user interface design and robot software architectures [37,43]. The differences between HRI and traditional human-computer interaction, considering complex, dynamic control systems, autonomy, and real-world environments. The proposed theory introduces five interaction roles: supervisor, operator, teammate, bystander, and mechanic, each with distinct tasks and situational awareness needs. The dimensions of mobile robots' physical nature, dynamic behavior, environmental challenges, the number of systems users interact with, and the robot's autonomy are discussed. [44]

Real-time movement adaption using a proposed software architecture is emphasized in the focus on developing companion robots for physical interaction. Prioritizing comfort, safety, and socially acceptable behavior, grip planning is discussed, with a focus on double grasps in human-robot interactions. Real-time trajectory changes based on cubic functions are used to address motion planning issues, and an attentional system is used to strike a compromise between task efficacy and safe interaction. The ultimate goal is to create manipulator robots that are safe, intuitive, and able to work together in shared workspaces [45,46]. The difficulties in ensuring safety as well as appropriate degrees of trust in human-robot interactions must be taken into account in order to increase safety, particularly in home and healthcare settings where robots can communicate with vulnerable populations without professional supervision. It brings up moral questions regarding how to do safe and realistic experiments on trust without endangering subjects [47].

Examining the critical role that machine learning algorithms play in HRI, on signal interpretation and communicative action generation across many channels, including touch, sight, and hearing. Obstacles and advances in each domain and highlights the importance of benchmarking for performance evaluation of interactive robots. In order to achieve market acceptance, it emphasizes the necessity of certification procedures and stresses the importance of taking psychological, social, and practical factors into account when creating effective HRI communication. The information offered clarified the state of social robot development and the possibility of their commercialization [48]. Furthermore, an investigation into the hand-over task using wooden cubes indicates that human-to-human interactions can exhibit adaptive learning, as seen by a consistent reduction in hand-over duration across trials. The use of a minimum-jerk profile by a humanoid robot during the hand-over resulted in much shorter reaction times in robot-human interactions, highlighting the significance of imitating biological motion. Although there are some discrepancies, the study indicates that human-robot hand-over interactions can be made efficient and predictable by present robot technology, which can lead to the development of efficient joint-action techniques in humanoid robot systems [49].

Challenges and considerations in developing courses on HRI for computer science and engineering students. Recognizing the multidisciplinary nature of HRI and the lack of standardized educational materials. It addresses challenges such as the diversity of the field, the lack of dedicated resources, and the need for cost-effective robots and outlines suggested course content, including topics like emotion, ethics, robot design, and social behaviors. Emphasizing the necessity of a statistical background and the importance of considering industry needs in course development. The findings aim to contribute to the ongoing discussion and development of HRI education [50].

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Researchers have been using hashtags to build training datasets for emotion identification in brief communications in recent studies investigating applications of NLP. Unigrams outperformed bigrams and trigrams, reaching approximately 65.12% accuracy, in the studies, which underscore the difficulties of distinguishing emotions in brief textual content and the possibilities of using social media data [51,52]. An additional sophisticated framework is dedicated to the extraction of emotions from multilingual text data on social media, with a specific focus on political elections, medical events, and sporting occasions. Emotion theories and machine learning methods are combined in this framework, which has been shown to improve affective interfaces and ease decision-making [51,52].

The oil and gas industry's use of industrial robotics highlights the need for further automation in challenging conditions. The limitations of conventional industrial robots are discussed, with a focus on issues of adaptation and worries about trust, accountability, and organizational integration in situations where humans and robots work together or are replaced [35]. A study investigates the physical ranges and orientation between human users and service robots, focusing on co-presence and embodied engagement in (HRI. Results highlight how important spatial awareness is for creating socially acceptable robots, urging more research into behavior patterns and design improvements [63].

An NLP-based study looks into the emotional aspects of conservation issues with the reintroduction of wolves in Saxony, Germany. Anger (74%) and fear (36%) are the most common negative emotions seen in news items, and they are linked to important stakeholders like farmers and hunters. The study highlights the influence of news organizations on public attitudes and argues for a more balanced portrayal of human-wildlife interaction [35]. An additional interdisciplinary project analyzes how NLP, human-computer interaction, and mental health research connect, with a particular focus on NLP methods for leveraging social media data to assist mental health. The review emphasizes cooperation and a common language among researchers by providing a taxonomy of data sources, methodologies, and interventions [64,65].

Machine learning plays a key role in human-robot communication, especially when it comes to processing information from accelerometers, touch sensors, voice recognition software, and image material. For voice commands and sophisticated speech-controlled apps to integrate seamlessly, behaviour generation including planning and execution is necessary [48,66]. Developments in data accessibility, computational power, and machine learning have led to investigation in applications including image-to-text generation and social media content production, demonstrating the growing interest in NLP across a range of areas. According to the survey, multidisciplinary work requires more cooperation with different disciplines [67].

Evolving as an interdisciplinary area, Socially Assistive Robotics (SAR) focuses on creating robots that assist in social interactions. SAR emphasizes safe, moral, and productive interactions and offers potential as a therapeutic technique for a variety of populations [18]. The combination of NLP and computer vision helps people with vision problems; these applications can be used in the real world [68,69]. The development of NLP-based social robotics research over the course of two decades reveals a difference between "Hard HRI" and "Soft HRI," indicating ongoing progress in the field [68,69].

Furthermore, the incorporation of NLP methods into social robotics improves verbal communication; this highlights the fact that social robots currently rely on crude language generation, and it suggests that NLG researchers and developers work together to create more complex interactions [70,71]. NLP is used to extract user data, interests, and hobbies for tailored interactions in an extensive conversation system that is proposed for natural engagement with social robots. Experiments with college students validate the potential of NLP in user modeling for socially intelligent robots, as shown by the adaptive conversation system [70,71]. Table 2 covers significant factors for conveying emotions and emphasizes the significance of various modalities in affective computing. Human communication relies heavily on facial expressions, body language uses postures and gestures to give significant emotional indications, and voice uses timing, loudness, and pitch to transmit emotions.

Table 2. Different modalities in affective computing.

Modality	Importance in Affective Computing	Influential Parameters for Expressing Emotions	
Facial Expression	Most crucial component in human communication	N/A	[18,53,54,55,56]
Body Language	Provides strong and reliable cues to emotional state	Whole body static postures, whole body movement, gestures	[18,57,58,59,60]
Speech	Significant in expressing emotions	Pitch (level, range, variability), timing, loudness	[18,61,62]

Challenges with ChatGPT HRI and NLP

Prompting LLMs for robotics control poses several challenges, such as providing a complete and accurate description of the problem, identifying the right set of allowable function calls and APIs, and biasing the answer structure with special arguments [3,18].

First, we define a high-level robot function library. This library can be specific to the form factor or scenario of interest and should map to actual implementations on the robot platform while being named descriptively enough for ChatGPT to follow. Next, we build a prompt for ChatGPT which describes the objective while also identifying the set of allowed high-level functions from the library. The prompt can also contain information about constraints, or how ChatGPT should structure its responses. The user stays in the loop to evaluate code output by ChatGPT, either through direct analysis or through simulation, and provides feedback to ChatGPT on the quality and safety of the output code. After iterating on the ChatGPT-generated implementations, the final code can be deployed onto the robot [3].

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Microsoft is looking into how ChatGPT can make it easier to program assistive robots. Non-technical users may give high-level input in plain English to ChatGPT, which then generates Python code for the robots instead of engineers physically constructing code. This method does away with the requirement for deep coding knowledge, making programming simpler and efficient [3]. Chat-GPT models can now understand text messages and produce responses that mimic those of a human. With the use of this natural language learning, the robot is able to carry on logical conversations with users, interpreting spoken and typed inputs while keeping the interaction within context [72].

ChatGPT is limited by the fact that it was trained on a limited dataset, which leaves it vulnerable to biases and mistakes in language interpretation. It might not work well, for instance, if it has been trained to anticipate a given value for a place but meets an unexpected one. It can, however, behave appropriately if provided with the relevant information. This highlights how crucial it is to thoroughly plan and verify user manuals before deploying ChatGPT. It is important to consider and deal with these challenges when developing models that rely on language models, such as ChatGPT, for human-robot interaction [73-77]. Table 3 below shows a list of robot that are being built for research with various functionality and uses that are making our everyday life fun and easier.

Table 3. Different types and uses of robots.

Robot Name	Type	Function	Uses	
Kismet	Expressive Robot with "Social Intelligence"	Eliciting normal social interaction, especially with children	Human-robot interaction, social interaction, expressive capabilities	[78,79]
MR Helper (Mobile Robot Helper)	Physical Interaction Robot	Dual manipulators for cooperative object manipulation	Assisting in daily tasks, medical applications, and home automation	[80-83]
DR Helpers (Distributed Robot Helpers)	Physical Interaction Robot	Transporting objects in collaboration with humans	Assisting in daily tasks, collaborative object transport	
MS DanceR (Mobile Smart Dance Robot)	Physical Interaction Robot	Capable of dancing the waltz as a partner	Entertainment, fine coordination with a human during dancing	[80,81,84]
Wakamaru	Humanoid Robot	Studying human-robot proxemic behavior, investigating physical and psychological distancing	Guiding the design of robots integrating into human environments	[16,85,86]
ASIMO	Humanoid Robots	Interactions with university students in various conditions, assessing subjective impressions and behaviors associated with each entity	Human-robot interactions, subjective impressions, nonverbal behaviors	[87,88]
Autom	HCI-based Sociable Robot	Weight loss coach, compared impact with a standalone computer and a paper log in a controlled study	Long-term human-robot interaction, promoting successful weight loss and maintenance	[24,89-91]

Conclusions

The future of AI creativity emphasizes the widespread adoption of AI skills across industries and the collaborative creation between humans and AI. It highlights educational initiatives making AI education inclusive, addresses challenges like pre-mature AI technologies and security issues, and stresses the importance of exploring AI education systems. The article also advocates for integrating liberal arts with AI, fostering both AI thinking and skills, and ultimately democratizing AI and creativity. Despite the cons and pros of ChatGPT-based HRI, many things can be considered for further study and improvements. Improved AI models as AI technology continues to advance, we can expect more accurate and reliable models that minimize biases, better understand context, and provide even more valuable assistance to researchers. However, the reliability and safety must be carefully examined to avoid potential hallucinations or harmful unintended outputs. ChatGPT could be trained to learn from its interactions with users, and continually improve its responses and capabilities. NLP models can enhance the understanding of psychotherapy processes and emotions, providing a potential alternative to traditional methods. Limitations include the need for clearer emotion definitions and instructions. The findings offer implications for research, supervision in clinical practice, and the potential of NLP in advancing psychotherapy science. The significance of customer support and the application of NLP and AI, particularly chatbots, to enhance communication efficiency. Its primary aim is to develop an AI agent for automatic chat conversation generation using NLP and deep learning. Evaluation metrics such as BLEU score and cosine similarity validate LSTM's superior performance. NLP's crucial role in reducing call center reliance is highlighted, focusing on IT customer service chatbots. This method of learning can be further integrated with robots for better interactions. In a

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nutshell, ChatGPT's integration with HRI has the potential to completely transform how humans interact and work with robots. Robotic conversations become more natural and approachable because of ChatGPT's natural language production and understanding capabilities. Ongoing attention is necessary to address persistent difficulties such as ethical considerations, biases, and contextual knowledge. In human-robot interactions, ChatGPT's capacity to decode requests from users and offer informative responses improves the user experience overall. With ongoing research and development aimed at addressing the current obstacles, ChatGPT and HRI's collaboration might be a key factor in creating a future where people and robots work together seamlessly to improve productivity and convenience. The route to improving these technologies is a dynamic one that might lead to the emergence of a new age of intelligent and compassionate human-robot communication.

Disclosure statement

No potential conflict of interest was reported by the authors.

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