International Journal For Advanced Research In Science & Technology
A peer reviewed international journal
ISSN: 2457-0362
www.ijarst.in

# EMOTION DETECTION AND RESPONSE IN SOCIAL ROBOTS (USING AI TO DETECT HUMAN EMOTIONS AND RESPOND ACCORDINGLY FOR CAREGIVING OR CUSTOMER SERVICE ROLES

**Ivan I. Anya[1], Sujata Vijay Shinde[2], Samudra Syarif Wahyu Hidayatullah[3]**

[1,2,3]Subject Matter Expert, Kazian School of Management, Mumbai, India
iivananya@yahoo.com, sujata.vijay.shinde@gmail.com, samudrasyarif@gmail.com

## ABSTRACT

*This paper examines several methodologies for emotion recognition, including both conventional techniques and contemporary AI-driven frameworks, and analyzes how these systems facilitate real-time tailored replies from robots. The research underscores the potential of emotion-aware robots to enhance healthcare, hospitality, and customer service, highlighting the need of empathy, flexibility, and social intelligence in facilitating productive interactions. This article examines current progress in emotion identification methodologies in Human-Robot Interaction (HRI), concentrating on the development of perception-based, electroencephalogram (EEG)-based and multimodal fusion methods. Emotion recognition is becoming an important aspect of making robots more emotionally intelligent, which means they can better understand and react to human emotions, especially in healthcare and service settings.*

**Keywords: -** Emotion, Robots, Human, Machine Learning, Customer.

## I. INTRODUCTION

Detecting and responding to emotions in social robots is a groundbreaking combination of AI, robotics, and human-computer interaction that changes the way machines comprehend and interact with people [1]. Social robots can understand complicated human emotions and react in ways that seem natural and caring by using AI-powered systems that can recognize facial expressions, speech patterns, body language, and physiological signs. This skill is especially important in caregiving and customer service situations, where being able to read emotional signals is key to enhancing the user experience, delivering prompt help, and building trust [2]. For example, emotionally intelligent robots may keep an eye out for indicators of sadness, loneliness, or anxiety in healthcare or eldercare settings and take appropriate action, such as having a consoling conversation or letting human caregivers know when they need to. These robots can tell whether a consumer is angry or confused and change their tone and way of talking to them. They can also provide individualized help, which makes customers happier, more efficient, and more loyal [3].

Computer vision for face identification, natural language processing for sentiment analysis, and machine learning algorithms that can combine data from several senses to provide a complete picture of a user's emotional state are some of the technologies that make this emotional intelligence possible [4]. Recent progress in deep learning, like convolutional and recurrent neural networks, has made it possible to find small cues like micro expressions or changes in tone in speech. Reinforcement learning, on the other hand, lets robots change how they respond over time based on how people interact with them [5]. In addition to technical skills, building the right replies for robots involves a deep grasp of social norms, cultural variations, and ethical issues. This makes sure that interactions are helpful, not invasive, and safe for users' mental health.

Emotion-aware social robots have effects that go well beyond just being new technology. In caring, they provide practical answers to problems caused by an aging population, a lack of caregivers, and rising mental health demands [6]. They also provide companionship and monitoring that improves overall health. In customer service, they make interactions between people and machines more understanding and flexible, which cuts down on conflict and improves service delivery. The addition of emotion recognition and response behavior to robots marks a move toward machines that are not just efficient but also socially aware, able to develop trust, emotional resonance, and meaningful interactions with people [7]. As research progresses, the potential for emotionally intelligent social robots to facilitate caregiving, improve commercial interactions, and enhance daily human experiences underscores the significance of interdisciplinary collaboration, ethical design, and the pursuit of human-centered innovation in the era of AI.

## Emotion Detection

Affective computing, often called emotion detection, is the process by which computers use AI and other approaches to figure out what people are feeling and how to react. Emotions are a very important part of how people talk to each other [8]. They affect how people make decisions, behave, and connect with others. For intelligent systems to be able to naturally and empathetically communicate with people, they need to be able to accurately recognize emotions. Modern emotion recognition systems use a mix of several types of information, such as facial expressions, speech patterns, body position, gestures, physiological signs, and text-based communication. Facial expression analysis, a prevalent methodology, employs computer vision algorithms and deep learning techniques, including convolutional neural networks (CNNs), to identify micro-expressions, muscle movements, and nuanced alterations in facial features that reflect emotional states such as happiness, sadness, anger, fear, surprise, and disgust [9]. Speech and voice analysis works with visual detection by looking at tone, pitch, volume, rhythm, and speech rate to figure out how someone is feeling. It commonly uses natural language processing (NLP) and recurrent neural networks (RNNs) to find trends across time and in different contexts. Body language and gestures provide more information and motion capture and pose estimation methods help look at posture, movement dynamics, and hand or arm motions. These are particularly useful when face or voice data is restricted. Wearable sensors may also capture physiological signs like heart rate, skin conductivity, and brain activity. These signals can be combined to find out how stressed, anxious, or aroused someone is, giving us a better overall picture of their emotional state [10].

Multimodal emotion detection is the process of combining input from many diverse sources into one system. This is becoming more and more crucial for improving accuracy and dependability since emotions are complicated and people express them in various ways in different situations [11]. These systems rely heavily on machine learning techniques, especially deep learning models, to pull out useful information from big datasets and guess people's emotional states in real time. Supervised learning methods need labeled datasets with examples of different emotional expressions. Unsupervised and reinforcement learning methods, on the other hand, let systems change and improve their predictions depending on new or changing emotional inputs [12]. Also, sentiment analysis in written communication like social media postings, emails, or chat messages employs NLP techniques to figure out the emotional tone of the writing, which makes emotion detection even more useful in human-computer connection. Even though there have been big improvements, there are still some problems to solve. These include recognizing subtle or mixed emotions, understanding how different cultures and people express their emotions, and dealing with noisy or missing data from real-life situations. Ethics are also very important since emotion detection technologies need to protect privacy, have permission, and be used responsibly, especially in sensitive areas like healthcare, mental health, and customer service [13].

Emotion detection has several uses, such as improving how people and robots interact, providing tailored customer service, helping with mental health monitoring, and making learning systems more flexible. In social robotics, effectively recognizing human emotions allows robots to react with empathy by changing their words, gestures, and behaviors based on the emotional context. This makes people more engaged, builds trust, and makes them happier with the service [14]. In healthcare and caregiving, being able to tell how someone is feeling may help you see indications of stress, sadness, or anxiety early on, which can help you plan treatments and improve the patient's health. Businesses utilize emotion detection in the business world to change their marketing, customer service, and user experiences depending on how people feel in real time. In general, emotion detection is a key step toward making intelligent systems that are not only useful but also socially aware. These systems should be able to understand human emotions and respond in ways that are appropriate for the situation, emotionally sensitive, and morally responsible. This is a big step forward in the development of human-centered artificial intelligence [15].

**Social Robots**

Social robots are machines that can work on their own or with some help from people. They are made to interact with people in a manner that is socially significant, imitating human interactions and behavior to encourage communication, cooperation, and emotional connection. Social robots are different from traditional industrial or service robots because they are made to work in places where people are, like homes, hospitals, schools, offices, and public places. In these places, interaction, empathy, and adaptability are very important [16]. These robots use new technology in artificial intelligence, machine learning, natural language processing, and sensors to see, understand, and react to how people act, feel, and communicate with each other. Social robots can talk and understand speech, read facial expressions, recognize gestures, and make decisions based on the situation. This lets them communicate naturally, understand social norms, and change their behavior based on what the users need and how they feel. Social robots can do a lot of different jobs by combining these skills. They can be educational assistants, therapeutic companions, customer service agents, and caring aids, among other things. They can also help meet human needs with technology [17].

The creation of social robots is based on research from several fields, including robotics, cognitive science, psychology, and human-computer interaction. This study shows how important empathy, engagement, and trust are in human-robot interaction [18]. For example, social robots made for healthcare and eldercare need to be able to recognize and react correctly to feelings like worry, loneliness, or agitation by employing behavior, voice tone, and gestures that provide comfort, reassurance, or encouragement. In the same way, social robots may improve learning and treatment results in schools and therapy by giving each student or patient individual attention, positive feedback, and incentive. In customer service, social robots act as interactive agents that can tell when a user is frustrated, confused, or happy, and change their responses and actions in real time to make the experience better and the service delivery more efficient [19]. To be able to adapt in this way, social robots use a variety of sensors, such as visual cameras, microphones, tactile sensors, and wearable devices. These sensors send information to AI-driven models that analyze social and emotional signals, come up with appropriate responses, and keep learning from interactions to get better over time.

Social robots have a lot of promise, but they also have a lot of technological, social, and moral problems to deal with. It is still hard to accurately understand and analyze human emotions since people express them in different ways, emotions might be subtle or mixed, and data can be noisy or incomplete. It is just as hard to design robot behaviors that strike a balance between empathy and social standards. This is because acts that are too human-like or answers that are too rude might make people uncomfortable, distrustful, or less interested in using the robot. Ethical issues, including privacy, data security, user permission, and the risk of emotional reliance, are paramount, especially in the deployment of social robots within delicate contexts such as healthcare or childcare. Nonetheless, continuing study continues to tackle these issues, concentrating on enhancing multimodal sensing, adaptive learning algorithms, and human-centered design concepts to elevate the dependability, safety, and emotional intelligence of social robots.

## II. ADVANCING HUMAN–ROBOT INTERACTION THROUGH EMOTION RECOGNITION METHODS

As human-robot interaction grows quickly in many areas, recognizing emotions has become an important part of making interactions between people and machines more natural. Emotion recognition not only helps robots comprehend how people feel, but it also lets them change how they act depending on how the user feels. This is especially significant in fields like healthcare, customer service, and collaborative robotics. Right now, there are three main types of emotion detection methods used in HRI: Conventional ways of detecting emotions based on perception, physiological emotion identification based on electroencephalogram (EEG), and multimodal emotion detection methods [20].

**Conventional Methods for Emotion Detection**

Conventional approaches for recognizing emotions depend mostly on external cues that can be seen, such facial expressions, speech messages, and body language. Facial expression recognition, which looks at how certain facial muscles move to figure out how someone is feeling, has been extensively utilized in HRI for emotion identification. This approach uses Ekman's theory of facial expressions to find fundamental emotions like anger, pleasure, and sorrow. This gives robots an intuitive way to understand how people feel. For instance, Author has shown that facial expressions may aid service robots in discerning consumers' emotional reactions, hence enhancing service quality.

Nonetheless, facial expression recognition methods encounter challenges in intricate or obstructed settings. Author said that facial expressions don't always show how someone really feels. Users may hide their genuine feelings because of societal standards or pressure from their surroundings. Researchers have so transitioned to speech recognition methodologies, examining tone, speech tempo, and volume to enhance the precision of emotion identification. Voice signals that include emotional information may greatly improve HRI, particularly when visual clues aren't accessible or aren't dependable.

Traditional facial expression and speech recognition techniques are important for detecting emotions, but they only work with one kind of input, which makes them less useful in situations where there are many different types of interactions. This is why researchers are looking for more advanced ways of recognizing emotions.

**Emotion Detection Using EEG Signals**

Physiological signals, especially EEG-based emotion detection algorithms, have become more popular in the area to make emotion recognition more accurate and reliable. Emotions affect brain activity at the neurological level, and EEG readings may pick up on these changes in real time, which makes them a great way to tell how someone is feeling. EEG-based emotion detection in HRI is advantageous due to its capacity to identify nuanced emotional states, particularly when facial expressions or vocal signals are not clearly presented [21].

Deep learning models for EEG-based emotion identification have made a lot of development in the last few years. For example, Author has suggested the Source-guided Multi Target Learning model, which uses the variances in EEG signals from different regions to accurately identify emotions. This approach captures more complicated emotional patterns than standard techniques and works well in HRI applications where quick responses are important. Author further improves the model's capacity to analyze temporal sequences of data by mixing EEG with recurrent neural networks (RNN). This makes it faster and more accurate at detecting emotions.

Even while EEG-based emotion detection is more accurate than conventional approaches like facial and speech recognition, it still has several problems. First, the fact that EEG equipment may be worn might make users uncomfortable and change the way they interact with others. Second, the fact that brain signals vary from person to person means that emotion recognition models need to be very individualized and flexible in order to get consistent results.

## Integrated Approaches to Emotion Recognition

Multimodal emotion detection approaches combine many types of sensory information, such facial expressions, speech, and EEG data, to make emotion identification more accurate and reliable. Multimodal techniques get over the problems that single-modality methods have by mixing information from several modalities. For instance, EEG signals might provide extra information when visual signals are inconsistent or speech is unclear, making sure that emotions are always detected [22].

Recent research has shown that using more than one method may greatly increase the accuracy of recognizing emotions. Writer research integrated audio, text, and facial expressions to create a cross-modal emotion detection model that dramatically improved the accuracy of recognizing emotions in conversations. Finally, the Multimodal Fusion Network (MMFN), which combines touch movements and facial expression data, came up with a new framework that made it much easier to accurately identify emotions in complicated interactions.

The Interactive Emotional Dyadic Motion Capture (IEMOCAP) dataset is a standard for testing multimodal emotion recognition systems. It is used to compare approaches including voice, facial expression, text, and multimodal fusion techniques.

Based on IEMOCAP findings, Table 1 shows how accurate and useful certain emotion identification algorithms are.

**Table 1: Comparison of Emotion Detection Techniques on IEMOCAP Dataset**

| Method | Data Type | Accuracy (%) | Applicability |
|---|---|---|---|
| Facial Emotion Recognition | Motion Capture (Face, Head, Hand) | 48.99% | Suitable for clear facial cues in well-lit environments. |
| Speech Expression Recognition | Audio Signal | 55.65% | Effective for remote interactions or limited visual data. |

| | | | |
|---|---|---|---|
| Text Emotion Detection | Text (Transcr ipts) | 64.78% | Useful in conversations or textual dialogues. |
| Multimodal Fusion | Audio, Text, Motion Signals | 71.04% | Optimal in dynamic and complex interaction environments. |

EEG is the best model for identifying subtle emotional states that voice or facial clues typically miss. This makes it very useful for nuanced emotional analysis. Multimodal methods, which combine signals from several sources, always work better than single modality methods.

These systems use verbal, visual, and physiological data to make interactions between people and robots in changing surroundings more realistic and responsive.

## III. EMERGING TECHNIQUES IN AFFECTIVE COMPUTING

The subject of emotion identification in human-robot interaction has seen significant growth in recent years, driven by breakthroughs in algorithmic techniques and hardware innovations. This chapter examines these breakthroughs, emphasizing advancements in conventional emotion identification methods, the integration of deep learning in multimodal systems, and the contribution of hardware to the enhancement of real-time emotion detection [23].

### AI-Driven Multimodal Emotion Analysis

Deep learning has made a big difference in the area of emotion identification, particularly in systems that use more than one kind of input, such visual, aural, and physiological information.

Long Short-Term Memory (LSTM) networks and convolutional neural networks (CNNs) have proven very important for getting characteristics from big, complicated datasets. This has made emotion recognition systems more accurate and flexible.

One major new idea in this field is the use of Transformer-based models, which do better than older techniques by finding long-range connections across distinct modalities.

These models have been used to combine data from audio, text, and visual sources, which has made it easier to accurately recognize emotions in conversations. Park et al. say that using Transformers made it possible to combine numerous data streams in real time, which made it easier to identify emotions in human-robot interactions.

Another deep learning method that has worked well in emotion identification systems is multitasking learning. It enables a singular model to concurrently forecast several emotional states or personality characteristics, resulting in enhanced generalization across tasks and more effective data use.

International Journal For Advanced Research
In Science & Technology
A peer reviewed international journal
www.ijarst.in
ISSN: 2457-0362

These improvements are especially important for HRI applications that are dynamic and happen in real time, where systems have to constantly change to respond to different emotional inputs from users.

**Advances in Hardware for Emotion Detection**

Along with new algorithms, new hardware has also been very important in making emotion identification systems more useful. Wearable sensors, especially those that record electroencephalography signals, have gotten lighter and simpler to carry, which makes it easier to add physiological data to emotion identification systems.

These sensors provide real-time information on brain activity, which, when used with deep learning algorithms, makes it possible to more accurately guess emotional states in real-life situations.

Figure 1 shows how EEG-based emotion recognition works. It records brain activity in reaction to emotional inputs. Next, the raw EEG data is cleaned up to get rid of artifacts, and then essential brainwave frequencies are extracted from it. These characteristics are fed into an emotion detection model, which determines the user's emotional state (e.g., happy, neutral, sad) [24].

This combination of EEG sensors with emotion recognition algorithms makes it possible to accurately identify emotions in real time, which makes human-robot interaction even more successful in realistic settings.

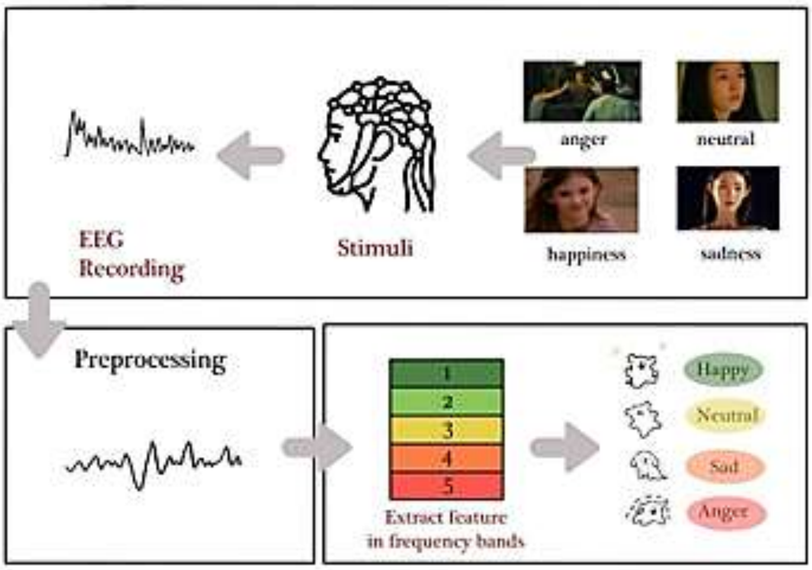


**Figure 1: EEG-Based Emotion Recognition Pipeline Using Stimuli and Frequency Band Feature Extraction**

Figure 1: The steps involved in recognizing emotions using EEG Also, memristive circuits have become a strong way to improve hardware-based emotion identification. Memristive

International Journal For Advanced Research In Science & Technology
A peer reviewed international journal www.ijarst.in
IJARST
ISSN: 2457-0362

circuits work like the brain when it comes to learning, which makes it possible to interpret emotional input more efficiently. This new idea makes it possible to use emotion detection algorithms on low-power devices like robots while keeping the processing speed high [25]. The development of brain-computer interfaces (BCIs) has also made it easier for people and robots to connect with each other. BCIs make interactions with robots more natural and caring by letting them get real-time emotional response from people via direct brain impulses.

## IV. EMERGING TECHNIQUES IN HUMAN EMOTION ANALYSIS

### Integrative Methods for Emotionally Intelligent Systems

In contemporary human-robot interaction, robots must not only discern human emotions but also react via integrated multimodal feedback systems. Emotionally intelligent robots get information from many places, such speech, facial expressions, and actions. They then change how they respond in real time to make the encounter seem more genuine and emotionally sensitive. These technologies improve the user experience by changing how robots act depending on real-time emotional inputs.

The researcher stresses how important it is for robots and people to be able to communicate with each other emotionally in both directions. By combining data from many sources, robots can better understand how people are feeling and provide them fast feedback that is relevant to the situation. This real-time emotional processing lets robots change how they interact with people and respond in ways that match the user's mood, which makes both engagement and user pleasure better. Additionally, the researcher emphasizes that robots may use organized emotional representations to refine their answers, so facilitating a more seamless emotional connection. Artificial Emotional Intelligence (AEI) should aim to replicate and enhance natural emotions—especially human emotions—to enable robots to identify and articulate emotions during Human-Robot Interaction (HRI) [26].

### Empathy and Emotional Feedback in Human–Robot Interaction

As social robots become better, empathy has become an important part of making interactions between people and robots better. Robots that can comprehend and react empathetically to human emotions are more likely to be embraced and included into sectors such as healthcare, education, and customer service.

Researchers provide a paradigm for creating sympathetic systems in social robots. This approach emphasizes the capacity of robots to augment emotional ties with individuals via proficient emotion detection and feedback. The researcher also talks about how emotional feedback in service robots may make the whole user experience better. This shows that robots that can understand and respond to people's feelings can greatly influence how people think about their interactions. These robots can help people feel more connected and happy in a number of different ways by reacting to their emotions.

## V. CONCLUSION

Using AI to identify and respond to emotions in social robots might greatly improve how people and robots interact, especially in caregiving and customer service. These robots can provide better, more customized, and more effective help by knowing and reacting to how people feel. As AI technologies become better, social robots will probably become more helpful and kind companions, making daily interactions more efficient and emotionally healthy.

**REFERENCES**

[1] Acosta-Enriquez, B. G., Arbulú Ballesteros, M. A., Huamaní Jordan, O., López Roca, C., & Saavedra Tirado, K. (2024). Analysis of college students' attitudes toward the use of ChatGPT in their academic activities: Effect of intent to use, verification of information, and responsible use. *BMC Psychology, 12*(1), 255.

[2] Borau, S., Otterbring, T., Laporte, S., & Fosso Wamba, S. (2021). The most human bot: Female gendering increases humanness perceptions of bots and acceptance of AI. *Psychology & Marketing, 38*(7), 1052–1068.

[3] Chi, N. T. K., & Vu, N. H. (2023). Investigating the customer trust in artificial intelligence: The role of anthropomorphism, empathy response, and interaction. *CAAI Transactions on Intelligence Technology, 8*(1), 260–273.

[4] Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340.

[5] Efthymiou, F., & Hildebrand, C. (2024). Empathy by design: The influence of trembling AI voices on prosocial behavior. *IEEE Transactions on Affective Computing, 15*(3), 1253–1263.

[6] Elmashhara, M. G., De Cicco, R., Silva, S. C., Hammerschmidt, M., & Levi Silva, M. (2024). How gamifying AI shapes customer motivation, engagement, and purchase behavior. *Psychology & Marketing, 41*(1), 134–150.

[7] Gao, L. X., López-Pérez, M. E., Melero-Polo, I., & Trifu, A. (2024). Ask ChatGPT first! Transforming learning experiences in the age of artificial intelligence. *Studies in Higher Education, 49*(12), 2772–2796.

[8] Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals, 14*(2), 627–660.

[9] Grundke, A., Stein, J.-P., & Appel, M. (2022). Mind-reading machines: Distinct user responses to thought-detecting and emotion-detecting robots. *Technology, Mind, and Behavior, 3*(1).

[10] Han, E., Yin, D., & Zhang, H. (2023). Bots with feelings: Should AI agents express positive emotion in customer service? *Information Systems Research, 34*(3), 1296–1311.

[11] Huang, M.-H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science, 49*(1), 30–50.

[12] Laux, J., Wachter, S., & Mittelstadt, B. (2024). Trustworthy artificial intelligence and the European Union AI Act: On the conflation of trustworthiness and acceptability of risk. *Regulation & Governance, 18*(1), 3–32.

[13] Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 46*(1), 50–80.

[14] Lee, M. K. (2018). Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management. *Big Data & Society, 5*(1), 1–16.

[15] Ma, Y. M., Dai, X., & Deng, Z. (2024). Using machine learning to investigate consumers' emotions: The spillover effect of AI defeating people on consumers' attitudes toward AI companies. *Internet Research, 34*(5), 1679–1713.

[16] Marcus, G. E., & Mackuen, M. B. (1993). Anxiety, enthusiasm, and the vote: The emotional underpinnings of learning and involvement during presidential campaigns. *The American Political Science Review, 87*(3), 672–685.

[17] Matthew, J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., et al. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, 1–9.

[18] Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. *The Academy of Management Review, 20*(3), 709–734.

[19] McKee, K. R., Bai, X., & Fiske, S. T. (2023). Humans perceive warmth and competence in artificial intelligence. *iScience, 26*(8), 1–29.

[20] Mehrotra, S., Centeio Jorge, C., Jonker, C. M., & Tielman, M. L. (2024). Integrity-based explanations for fostering appropriate trust in AI agents. *ACM Transactions on Interactive Intelligent Systems, 14*(1), 1–36.

[21] Mehrotra, S., Degachi, C., Vereschak, O., Jonker, C. M., & Tielman, M. L. (2024). A systematic review on fostering appropriate trust in human-AI interaction: Trends, opportunities and challenges. *ACM Journal on Responsible Computing, 1*(4), 1–45.

[22] Merrill, K., Kim, J., & Collins, C. (2022). AI companions for lonely individuals and the role of social presence. *Communication Research Reports, 39*(2), 93–103.

International Journal For Advanced Research In Science & Technology
A peer reviewed international journal www.ijarst.in
IJARST
ISSN: 2457-0362

[23] Moors, A., Ellsworth, P. C., Scherer, K. R., & Frijda, N. H. (2013). Appraisal theories of emotion: State of the art and future development. *Emotion Review, 5*(2), 119–124.

[24] Pantano, E., & Scarpi, D. (2022). I, robot, you, consumer: Measuring artificial intelligence types and their effect on consumers' emotions in service. *Journal of Service Research, 25*(4), 583–600.

[25] Pizzi, G., Vannucci, V., Mazzoli, V., & Donvito, R. (2023). I, chatbot! The impact of anthropomorphism and gaze direction on willingness to disclose personal information and behavioral intentions. *Psychology & Marketing, 40*(7), 1372–1387.

[26] Pollock, A., & Berge, E. (2018). How to do a systematic review. *International Journal of Stroke, 13*(2), 138–156.