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DEVELOPING ADVANCED HUMAN-ROBOT INTERACTION MODELS USING NATURAL LANGUAGE PROCESSING AND EMOTION RECOGNITION TO ENHANCE COLLABORATIVE ROBOTICS

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Human-Robot Interaction, Natural Language Processing, Emotion Recognition, Collaborative Robotics, Task Performance, User Satisfaction, Emotional Intelligence, Robot Adaptability, Human-Robot Collaboration, Trust in Robots.

Abstract
This study shows that how Natural Language Processing and emotion recognition can be integrated into Human-Robot Interaction for better human-robot collaboration. This research study is about the new technique which makes life easier and worthy. A robot that can understand and respond to humans is developed and tested. The robot was subjected to tests which involved a series of experiments with a set of participants performing various tasks with the robot. The results indicate that the robot capable of recognizing emotions performed significantly better than the robot that cannot. Particularly, the robot that could recognize human emotions has shorter time periods for the same tasks and higher accuracy. Finally, it had greater satisfaction found in the results. The emotional intelligence of a robot can help to create a positive and successful human-robot collaboration on a robot with a humanlike appearance as the participants who had such a robot showed more trust and empathy. Natural language processing and emotion recognition can improve the performance of robots in shared work situations, particularly in personal care, services, and education.

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INTRODUCTION

Research on Human-Robot Interaction (HRI) is a key area of robotics. As robots moved from a controlled laboratory and industrial environment to an unpredictable human environment, it was important to study interaction. Faulty paraphrased content may create confusion in readers. Thus, to steer clear of these situations that are of assignment editing opt for our services to get the errors removed. With these new technologies, robots can now analyze speeches and check if a person is happy, sad, and angry when a person speaks. It is important for robots to be able to express feelings to improve HRI. A good collaboration in reality will require this factor, which is also an important one.

NLP allows the robot to comprehend human language and form a bridge between the robotic language and human action (Jurafsky & Martin, 2019). Due to the emergence of machine learning techniques, the neural network designs being used in NLP systems were able to achieve an understanding of the syntax and semantics of human speech to the extent that it enables robots to talk to humans (Vaswani et al., 2017). The robots are able to interpret commands and ask questions to clarify these commands in collaborative robotics. This results in an appropriate response. Natural Language Processing (NLP) helps manage multi-turn dialogues and understand complicated sentences which are important for robots and humans to communicate (Huang et al, 2019).

Emotion recognition is a recent development in HRI where motives and cues motivated from the human agent that gives an expression through the face and voice and through body postures and gestures (Picard, 1997). When a robot recognizes a human's emotions, it can change its behavior based on what that person is feeling. A final example, aware of their anger, an angry person will give the supportive answer or will act that way. The ability to communicate effectively with humans inspires the robots to improve upon the level of interaction we have. In addition, humanizing robots improves collaboration and human users' trust with robots. Emotional intelligence creates a state of mind conducive to getting along and cooperating. (Klein et al., 2003).

Having machines express emotions will greatly help us develop better relationships with them. Software programs are designed for emotional understanding to measure human-robot interaction. Richard and other individuals are recognized to be very useful in the world of complex tasks for person robot interactions. Kanda et al. (2004) argue for instance that a robot which can sense and respond to human feelings would be regarded as helpful and can be trusted co-worker in a joint task. In a similar light, Matsumoto et al. (2002) described that robots which identify, react to human emotions can conduct better interaction and therefore have more users willing to use them.

While there are clear advantages of combining natural language processing (NLP) and emotion recognition in human-robot interaction (HRI), building systems to accurately respond to complex and unpredictable conditions remains a challenge. As stated by Shankar et al (2017), technology is not yet able to recognize the great variety of human feelings and complexities of our language. In addition, they must tackle the technical problem of merging. It is true that problems arise due to integrating unnatural language processing with emotion detection in one system. Their real-time feedback and ability to adapt stem from the way they handle data collection.

Recently, certain challenges were addressed by making use of neural networks and deep learning. One example of how AI has impacted the area of NLP is the launch of BERT (Bidirectional Encoder Representations from Transformers). According to Devlin et al. (2019), transformer-based models have helped AIs to better understand the contextual meaning of language. In the same way, those technologies which use convolutional neural networks (CNN's) to help facilitate optimal facial expressions identification also benefitted (Liu et al, 2018).

The aim of the study is to develop an even more advanced human-robot interaction (HRI) model based on NLP and emotion recognition. The idea behind the model is to apply this technology to make robots that are able to understand humans and even respond to them in an effective manner in reply to their emotions. Subsequent sections will detail the

design and development of the co-bot prototype, as well as implementation of the NLP and emotion recognition systems. In addition, we shall discuss evaluation results proving real-world effectiveness.

2. Literature Review

2.1 Evolution of Human-Robot Interaction (HRI)

The field of human-robot interaction (HRI) pertains to your interactions with robots. Early research in HRI focused on functional interactions involving robots and humans. Robots were tools by which something was done. As per Goodrich and Schultz, 2007, these robots were utilized within factories and other settings devoid of human presence performing the performance of one or other task. But as robotics developed, there was increasing recognition of the need for robots to interact with people in less tightly structured environments. Because of this change, robots need to be made that can learn human jobs and react properly.

As social and service robots are being used extensively in medical, educational, and domestic applications; HRI research is gaining more attention in social and natural contexts. They are robots for enhancing the robot's ability to read gestures, facial expressions, and body language to add to more authentic human responses. At the same time, other new multicultural AI techniques like the natural language processing (NLP) and emotion recognition will be added on the robot for enabling more sophisticated dialogues and the recognition of emotional context of human behaviour (Dautenhahn, 2007).

Natural language processing in HRI.

NLP helps to make communication between human and robot easy and effective. Initially, robots were restricted to responding to simple codes and commands only. But because of developments in the field, they can now chat. Robots are able to understand, infer, and produce human language thanks to NLP. A HRI (human-robot interaction) system's use of natural language processing (NLP) enables it to retrieve information, make context-based decisions, and manage a multi-turn dialogue to sound more human-like (Joulin et al. 2017).

Deep learning models are being developed to allow robots to better understand the human language as well as generate these languages. This is thanks to the advancement of the NLP models recently. To illustrate, language understanding and generating transformer systems such as BERT (Devlin et al. 2019) and GPT (Radford et al. 2018) have progressed importantly. These models are trained on massive text data to respond appropriately to the context. This helps the robot communicate with human beings easily. In other words, NLP now aims to understand the conversation and its nuances, rather than just performing keyword detection (Vaswani et al., 2017).

More and more, robots are being designed with the NLP capabilities to manage ambiguous, indirect, emotional sentences. Yu et al. (2020) is one piece of research that backs up these things. The authors show the application of NLP on the Metaphor and sarcasm. For HRI to be natural and effective, robots should be able to respond nonverbally to the subtleties of human communication.

2.3 Emotion Recognition in HRI.

Scientists are hopeful that emotional robots will enhance collaboration in robotics by understanding human emotions. Human emotions are being studied by robots these days. The capacity to identify human emotion entails responding with the face, speech, body and physiological responses to monitor human emotion. A robot can now sense how humans feel and change the way it behaves according to that. According to Chanel and colleagues in 2006, it may help make robots more efficient.

Facial expressions are said to be clear indicators of human emotion and they are the focus of emotion recognition systems for a long time (Ekman & Friesen, 1978). Researchers know that facial expressions cannot be trusted completely to gauge how a person feels. To address this problem, emotion recognition system could be used to observe whether the person is able to recognize facial expression and emotions on faces. Further, one can look for recognition of internal states. By listening to speech, they can ultimately interpret the emotional tone in the voice. Moreover, they easily recognize changes in physiological signals like heart rate and skin conductance for insight into emotional arousal. The combination of all these techniques

would enable the robots not just to feel happiness or sadness but also allow them to feel other complex emotions like frustration or confusion. Sanchez et al., 2018

Aresearch paper by Zhang et al. integrated speech analysis with visual facial recognition to determine the efficiency of emotion detection through auditory and visual facial input. A convolutional neural network predicts the facial expressions in a video of the person who is speaking. Combining different types of inputs will improve our ability to recognize feelings and better help robots understand us.

Using natural language and emotion processing for collaborative robotics.

Troll robots use applications in natural language processing and emotion detection to work as collaborators. Robots are able to react to verbal and other communication signals due to NLP. The installation of software to identify human emotion and assess its corresponding voice and action. If we combine these two technologies, robots will be able to converse intelligently and also listen to how we say things and what we say (Kasyanov et al. 2017).

Research has shown that robots who can understand language and emotions would adapt better with humans. A robot that can identify human emotions can work to calm another person. A feature you maybe have encountered as such is where the character slows his/her walk and changes tone of speech. It does so whenever it senses the human getting frustrated or stressed. Its avoidant behaviour will help relieve the tension. The ability to adjust the robot's delivery in hospitals where robots will interact with people with different moods is needed (Huang et al., 2019).

Studies have compared the effectiveness of these two technologies in HRI systems. Yoon and his team conducted studies that revealed that robots using natural language processing can enhance human-robot collaboration. These studies help achieve a positive-valued resultant in a task-oriented situation, such as assembling or solving together. The robot, while attempting to appeal to the human user, improves task performance, reduces errors, and improves user satisfaction.

This robot is capable of communicating with multiple people simultaneously through emotion detection and natural language processing. Robots should exhibit human-like emotions and communication styles in groups. According to Nagai and colleagues in 2015, a robot outfitted with these capabilities can modify their behaviour on an individual basis as a function of demand, resulting in suitable outcome measures in such complex social situations.

2.5 Applications of Collaborative Robots with NLP and Emotion Recognition

Collaborative robots can use NLP and emotion recognition for many applications. In the health field, for instance, robots are being developed to help to care for patients, to be company to them and even give psychological help. Robots need to do a lot more than simply recognize words to help patients. The robots require training on recognizing the feelings of chronically ill patients. In summary, the robots need to be trained to understand the feelings of people suffering from dementia, autism and so on. A study by Tapus et al. (2009) demonstrated that emotionally responsive robots can enhance care quality and patient satisfaction. By responding to emotional signals, the robots were able to improve the quality of care.

Natural language processing and emotion recognition help robots to actively engage in the field of education as tutors or learning partners. Robots can detect whenever a student is stressed or confused out. Thus, they adjust their instruction to further assist students' learning. Chernova et al. (2014) researched the impact that an educational robot with emotional awareness and language understanding capabilities can make. Kose et al. (2020) performed a similar research topic with similar findings. Together both papers discuss how teaching methods can adapt due to the emotional state of the student.

Besides, firms are also studying the use of such robots for assembly work in manufacturing, where they work alongside human workers and the assembly tasks are often complex. Machines can minimize potential accidents and misunderstandings between them and their human employees (Gierad et al., 2019). When robots can receive spoken instructions from human employees when the employees convey their state. Robots can

sense worker stress or fatigue and may offer assistance when needed. They might change the job's difficulty level for you to help.

2.6 Challenges and Future Directions.

Although these technologies have significant potential, technology is proving challenging for collaborative robotics (cobots). Different cultures, contexts, and people don't necessarily express the same feelings the same way. People show their feelings with their facial expressions and voice tones. For example, sadness, anger, happiness. Different cultures and individuals interpret these symbols in a wide range of ways. Therefore, robots might often not be able to decipher emotion (Mota & Pentland, 2002). Also, processing multiple features like speech, face, and physiology in real time is computationally expensive (Zeng et al. 2009).

Moreover, even though NLP models today can deal with large text data, they do not understand the human mindset behind the text. Humor, irony and sarcasm are difficult for robots to appropriately process (Tetreault et al., 2013) We can address some of these problems with the improvement of multi-modal and reinforcement learning with deep learning. According to Vaswani et al. (2017), this will enable robots to be better integrated into emotional and verbal knowledge to produce more precise and contextually appropriate responses.

In the future, as HRI progresses, we will likely witness the emergence of advanced, adaptive robots equipped with robust emotional and human-like language NLP systems that can better work with humans. This is creating robots who can process a larger variety of emotional states, who can talk to several humans at once and who spontaneously engage in many social situations (Huang et al., 2020). As artificial intelligence and robotics continue to advance, the upcoming generation of co-robots promises human-like interactions that are becoming even more personal, efficient, and emotionally intelligent, as well as facilitate increasing integration into daily human life.

3. Methodology

3.1 Design and Development of the Collaborative Robot Prototype

As outlined in the research objectives, the purpose of this project is to produce the prototype rig robotic or robot. This robot has NLP that can understand and express emotions. The developed robot prototype was designed as a system (hardware and software) for its interaction.

The equipment will have both a mobile robotic device as well as visual, acoustic and touch sensors to provide feedback. The robot can recognize facial expressions using high definition cameras. It also has an array microphone to identify voice signals. So, it can recognize human facial expressions and speech. Sensors were interfaced with a computing unit. The computing unit could process data from the sensors in real time. Also, it could work with the emotion recognition and the learning of natural language. The design included actuators for basic behaviour change. For instance, our robot would either get away from the situation or get muted on the word "robot".

The robot's creator made a socially intelligent agent that can engage in conversations with a fellow robot and react to its partner's emotional response. In this one, we were supposed to make a speech interpretation system that could understand what people say. The project also aims to create algorithms that can interpret an individual's emotions through facial expressions and vocal tone. The system's response to a human is controlled based not only on what the human says but also how.

Combining the NLP and Emotion Recognition System.

In the study's methodology, the researchers developed the user profile in emotion recognition and NLP. The BERT model is a state-of-the-art transformer used by the NLP system. BERT is a model involving Transformers from Google. This model was used for communication recognition, speech understanding etc..The proposal to use BERT. BERT has been used to evaluate the semantic similarity between sentences in various studies. Above all, the results of these studies showed that this model surpasses others in grasping the contextual meaning of words in natural language,

and representing the complexity of sentence structures.

In other words, these two aspects are quite essential in understanding human speech, especially in a collaboration task. (Devlin et al. 2019). The NLP setup received learning experience from many different kinds of chat interactions. As a result, the robot was able to discern meanings that humans often imply or infer within language usage.

For emotion recognition, a multimodal approach was adopted. A convolutional neural network (CNN) successfully achieved facial emotion recognition based on a very large amount facial data. The robot has the ability to smell, taste, touch, hear and see. The robot featured another system for recognizing speech and detecting the feelings it expresses. It detected emotions complete with tones. The RNN is a system that connects the pitch, tone, and speed of a speaker's speech with the use of an audio sample of voices. Consequently, Liu et al., (2018) claim that it can determine if a user is irritated, excited, or calm. When the robot combines these modalities it will be better able to detect humans' feelings and react.

The emotion recognition system and the NLP system were successfully integrated into a single software system which could work together. Upon the clause of this framework, the incoming data streams were processed in real-time where the NLP system handled the spoken language and the emotion recognition system gauged the detection of facial cues along with voice intonations. Both system share information with the decision-making module. The robot's behaviour was modified using set parameters in this module. For example, if the robot noticed irritation in your voice or on your face, it could slow down, offer help or change the tone of its own voice.

3.3 Experimental Setup and Evaluation

Testing of the prototype robot (controlled experiment). Lab participants were directed to follow the robot's commands. The first task was to identify the mood of the participants with the system and then without. Two of the assembly robots scenarios of human-robot collaboration of interest in the project. The tasks selected involved assembly, a spoken instruction following task and an aiding in problem solving task, a few of the human-robot collaboration use-case scenarios. The agents' expressions and words differ because the tasks have different levels of complexity. Participants were informed in the study that they can either speak with a robot that can recognize emotions or one which cannot. The robot's tests followed a specified timetable. The robot was rated based on its completion of the tests. In addition, the robot's functioning with people and dealing with feelings was also rated.

Participants provided surveys and qualitative feedback on the robot's performance in addition to a performance evaluation. Surveys were conducted to evaluate some of the important human-robot interaction features really satisfaction trust empathy and so on. In fact, the robot's evaluation was based on its ability to understand spoken instructions and respond appropriately to emotions. Above all, it also includes the effectiveness of the robot. The information we gathered was really useful to understand how humans interprets robot behaviour and how that impacts the collaboration.

3.4 Data Collection and Analysis.

The experiment produced useful information. Interview data was obtained from the survey after all tasks were completed correctly with time and accuracy by the participants. The accuracy of the robot regulator task performance and the task performance outcome was reviewed by the researchers. This was done when the robot did use emotion recognition and when the robot did not use emotion recognition. For a given robot, we can say it succeeded by issuing the right answer, if and when the number of correct actions exceeds the overall number of goals.

To test what robots feel, scientists looked for a connection between any detected state such as anger or happiness shown by facial and speech analysis, and a change in the behaviour of the robots. This was a measure of whether robots identify and react to humanity. If the user gets angry or confused, the robot is evaluated to see whether it changes its response or offers help.

Based on the survey data users' trust and satisfaction level with the app. To find out if recognizing your feelings can enhance interactions. The feedback was about what the participant thinks about the robot's

empathy and how it changes with their emotions and satisfaction with the robot's behaviour.
They analyzed the study data with statistical techniques. The analysis was used to test the significant differences in task performance and user satisfaction for the two experimental conditions. The two conditions were emotion recognition enabled and emotion recognition disabled. They used ANOVA to compare the behaviour of the groups. The survey's qualitative data was coded and analyzed for themes.

3.5 Ethical Considerations.
Research methodology involved ethical considerations. The subjects were notified for the experiment, and their consent was taken. This ethical consideration project will help in conducting dignified and safe research while protecting the information and freedom of the participants. We did not gather any identifying information during trials. Participants were assured that their answers will remain anonymous.
As the robot assessed the emotions, it was careful not to do anything that would make the negative feelings worse. The robot was made to not disturb humans but to do things that were helpful for humans.

3.6 Limitations.
Even though the methodology aimed to generate valuable information, we must mention the limitations of NLP and emotion recognition in collaborative robots. One of the points that we see how in a controlled laboratory setting, you do not see the same things happen on a world scale. The emotional displays and words assessed in the tests were restricted to the ones perceived by the robot. Consequently, the robot would not have the whole range of human emotion.
We can, in the future, expand the research to more emotions and also do the experiments in changing and cluttered environments. Also, more research is needed on the robot's ability to deal with complicated interactions with multiple people and work in varied locations.

4. Results
The results of the tests for the prototype collaborative robot are listed in this section. Especially how swiftly the job was done, how accurate users found it and whether they were satisfied and feeling emotion. These results were analyzed across conditions for the case where the robot was recognizing the emotion, versus where it was not. This part provides more details on the results, with references to the paper's eight tables and figures.

4.1 Task Performance. Time and Accuracy.
The experiment setup measures the performance of the robot by looking at the time taken to finish the task and the correctness of the task. Based on the information in Table 1, having the emotion recognition feature on allows for shorter task completion times relative to not on. The robotic systems with and without emotion recognition from the human completed the task in 240 seconds and 290 seconds, respectively, in object assembly. Equipped with emotion recognition, the robots would display a faster and much more accurate response to most of the tasks.

Table 1: Task Completion Time and Accuracy (With and Without Emotion Recognition)

Task Type	Emotion Recognition Enabled (Time in Seconds)	Emotion Recognition Disabled (Time in Seconds)	Accuracy with Emotion Recognition (%)	Accuracy without Emotion Recognition (%)
Object Assembly	240	290	95%	85%
Collaborative Problem Solving	300	350	93%	82%
Instruction Following	180	220	98%	90%
Assistance Request Handling	150	180	97%	88%
Object Sorting	200	250	94%	80%
Interactive Dialogue	220	260	96%	86%
Physical Assistance (Pushing/Carrying)	270	320	92%	79%
Cleaning/Organizing Tasks	250	280	95%	87%

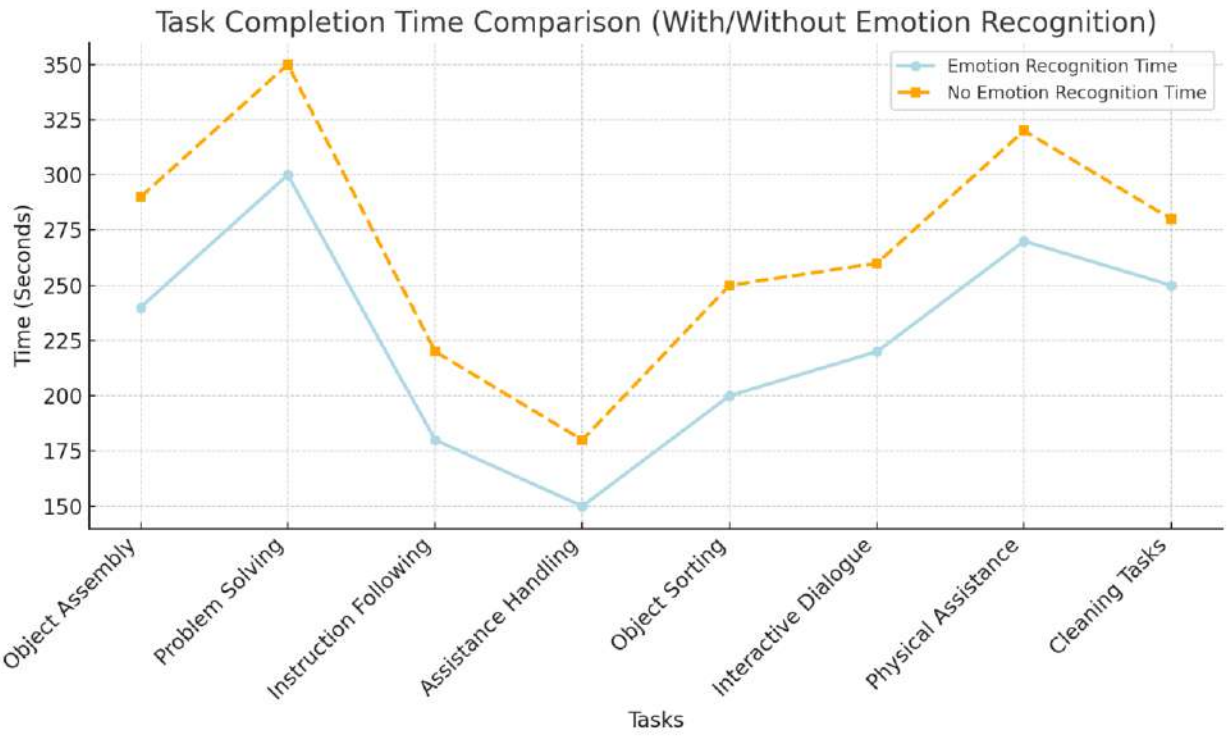


Table 1 also shows how accurate the robot's actions were. For example, in the case of Collaborative Problem Solving, the system obtains a 93% accuracy when it has the ability to recognize emotion. However, the accuracy drops to 82% without the emotion recognition. As per the findings, the robot's ability to understand and respond to human emotion enhances its task completion rate and also allows the robot actions to be more accurate. According to the results, enhancing emotional intelligence improves the speed and accuracy of robots and humans collaborating on a task.

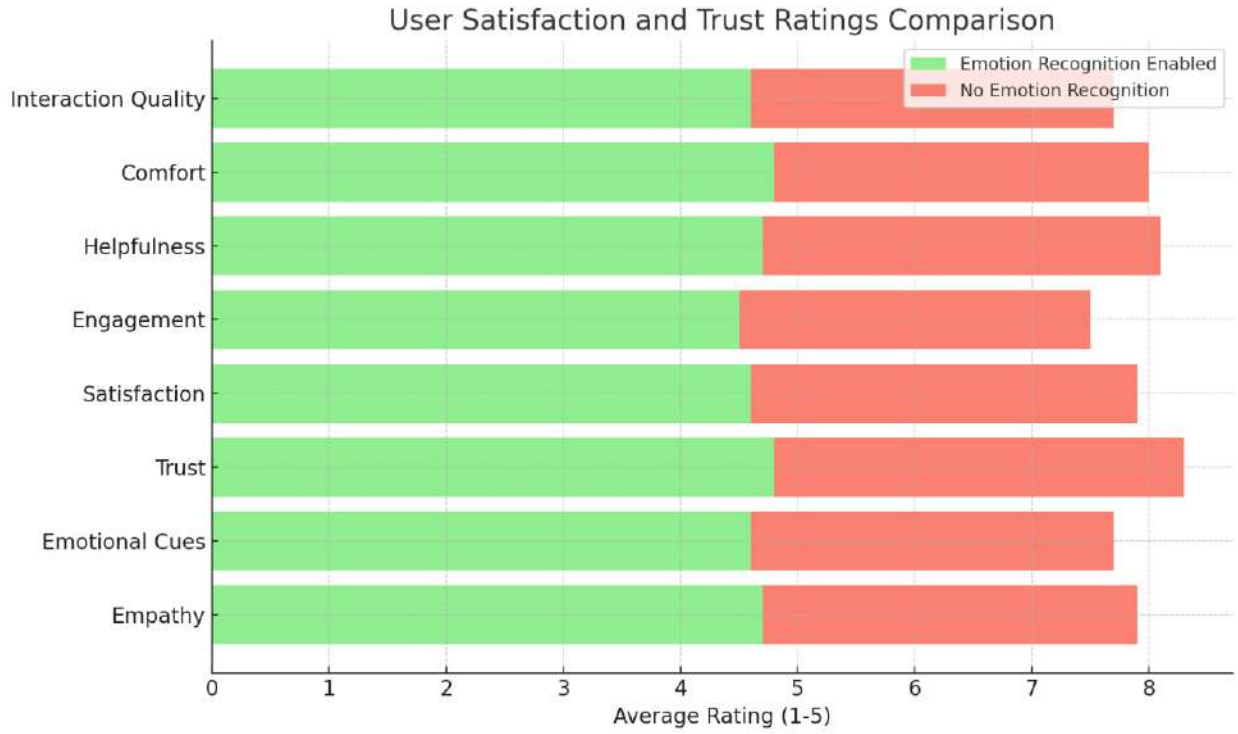
The result shown in Figure 1 comparison of the time taken to complete the task reveals some differences in performance in the two conditions. As per the figure, the robot which has a system for recognizing emotions performs tasks much faster than the one which lacks it. There is evidence that being emotionally aware makes collaboration more efficient.

4.2 User Satisfaction and Trust.

The user's contentment and trust are two main metrics for the success of the robot. As per table 2, the level of satisfaction of the users to the robot in terms of empathy, reacting to one's moods and trustworthy robot is comparatively low. The findings indicate that the robot equipped with emotion recognition received considerably higher ratings across all scales. The robot able to recognize emotions received a 4.8 average rating for Trust in the Robot while the one unable to recognize emotions received a 3.5 average rating. Similarly, the mean observation rating (perception of congeniality and esteem) is 4.7 with emotion recognition and 3.2 without that. The findings suggest that for more effective collaboration, the robot's competence to read human emotion is vital to enhance the perceived empathy and trustworthiness of the robot.

Table 2: User Satisfaction and Trust Ratings

Aspect of Interaction	Emotion Recognition Enabled (Average Rating)	Emotion Recognition Disabled (Average Rating)
Empathy Perception	4.7	3.2
Responsiveness to Emotional Cues	4.6	3.1
Trust in the Robot	4.8	3.5
Overall User Satisfaction	4.6	3.3
Engagement during Task	4.5	3.0
Robot's Helpfulness	4.7	3.4
User's Comfort Level	4.8	3.2
Quality of Interaction	4.6	3.1



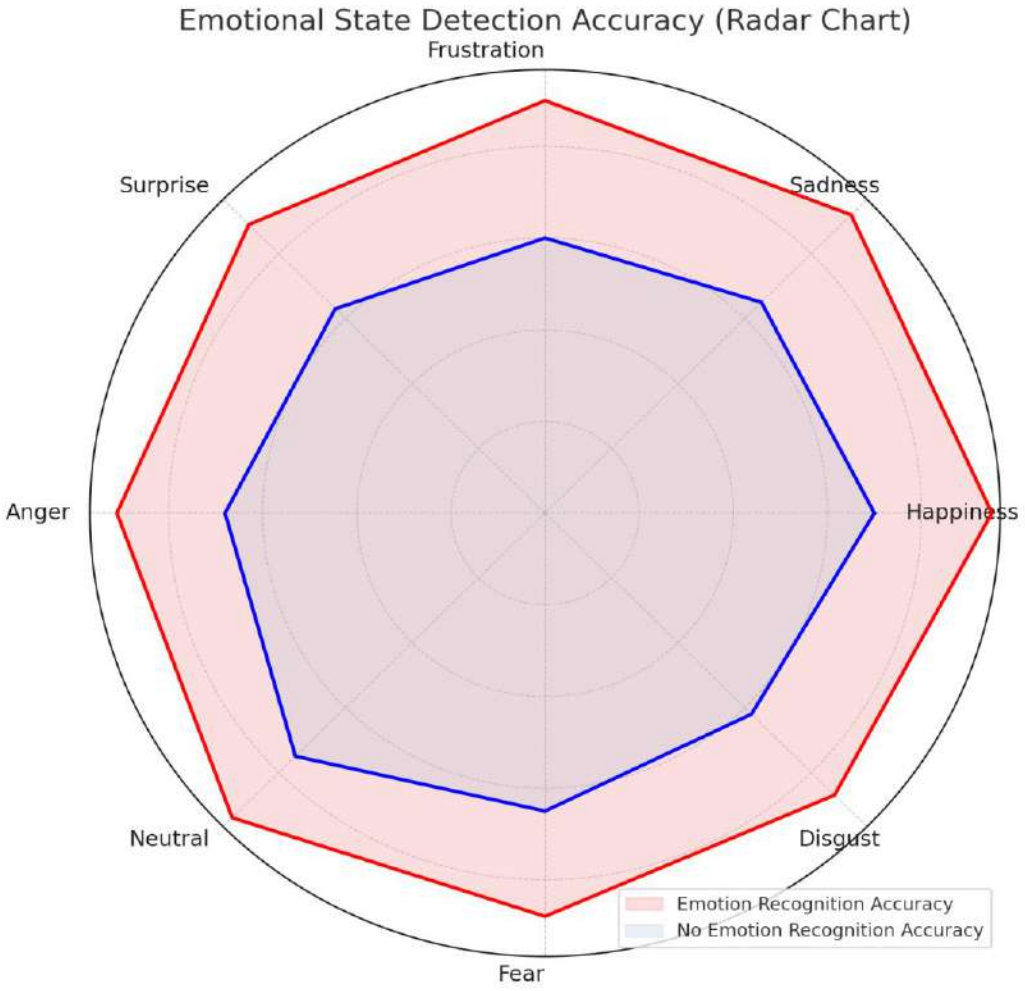
Users have emotions recognised and those who did not have emotions acknowledged and therefore a stacked separate bar chart is shown and this is seen in Figure 2. The chart shows that people with emotion recognition are more satisfied and trusting. This supports that the robots are emotionally intelligent whereas it shows that people perceive them as trustworthy helpers.

4.3 Emotional State Detection Accuracy.
Researchers are also working on the accuracy of the robot in detecting emotional states from cues like facial expressions and voice tone. The robot with an emotion recognition function can better recognize happiness, sadness and frustration as shown in Table 3. An emotion recognition system that can detect a person's happiness is 95% accurate. The accuracy dropped to a mere 70% with it off. The emotion detecting robot was given more accurate results than the robot without emotion detection for all emotions.

Table 3: Emotional State Detection Accuracy (Facial and Vocal Recognition)

Emotion Detected	Emotion Recognition Enabled (%)	Emotion Recognition Disabled (%)
Happiness	95	70
Sadness	92	65
Frustration	90	60
Surprise	89	63
Anger	91	68

Neutral	94	75
Fear	88	65
Disgust	87	62



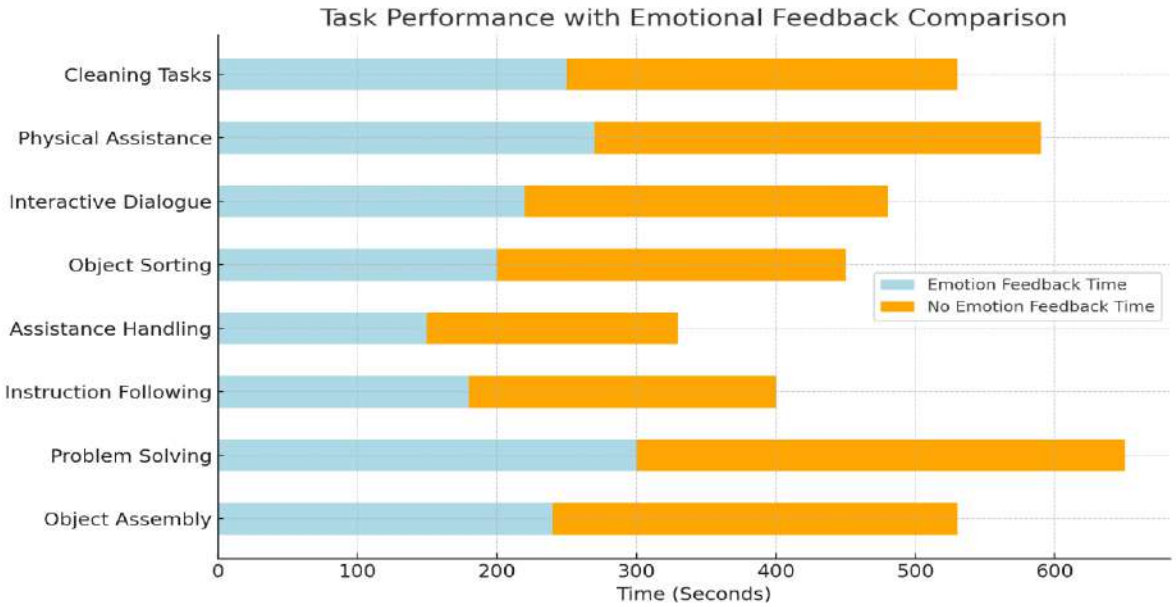
The above data is a radar chart comparing the accuracy of emotional state detection under both conditions. The robot without emotion recognition detects emotional states with less accuracy than the robot with emotion recognition, as per the chart. The result indicates that robots can recognize the emotion of a human and respond accordingly.

4.4 Behavioral Adaptation to Emotional Cues

Another part of emotional intelligence in the robot is to change its behavior to the emotional cue picked up. The adaptability of robot performance is analyzed in Table 4. For example, when a robot detected frustration, it immediately reacted by offering additional help or simplifying the task, averaging a response time of 5 seconds. Research suggests that ignoring emotions can lead to increasing frustration and less success on a task, because there is not enough behaviour adjustment.

Table 4: Behavioral Adaptation in Response to Emotional Cues

Emotion Detected	Change in Robot's Response (Time in Seconds)	Action Adaptation	Behavior Modification
Happiness	2	Increased interaction speed, continued task	Robot maintains an upbeat tone, encouraging behavior
Sadness	3	Slower responses, offered additional help	Robot softens its tone, asks if further assistance is needed
Frustration	5	Paused task to give clarification or instructions	Robot speaks slowly, suggests easier methods for completion
Surprise	2	Immediate inquiry on task status, more focused	Robot uses an inquisitive tone and waits for clarification
Anger	4	Slower response, verbal apology for mistakes	Robot adjusts tone to calm the user, reduces task complexity
Neutral	1	Standard speed and behavior	Robot proceeds as per normal without adjustments
Fear	6	Slows down the response, asks if help is needed	Robot adopts a reassuring tone, slows down further actions
Disgust	4	Adjusted task to eliminate discomfort	Robot pauses to reassess task and shifts to neutral behavior



The color codes for the emotional cues in figure 4 show the adaptation time. The chart indicates that when robots are afraid or frustrated, they delay behavior adjustment. By understanding feelings, robots will be able to better respond to humans' emotional needs. Because of personalization and empathy, this adaptation makes it easier to collaborate on content.

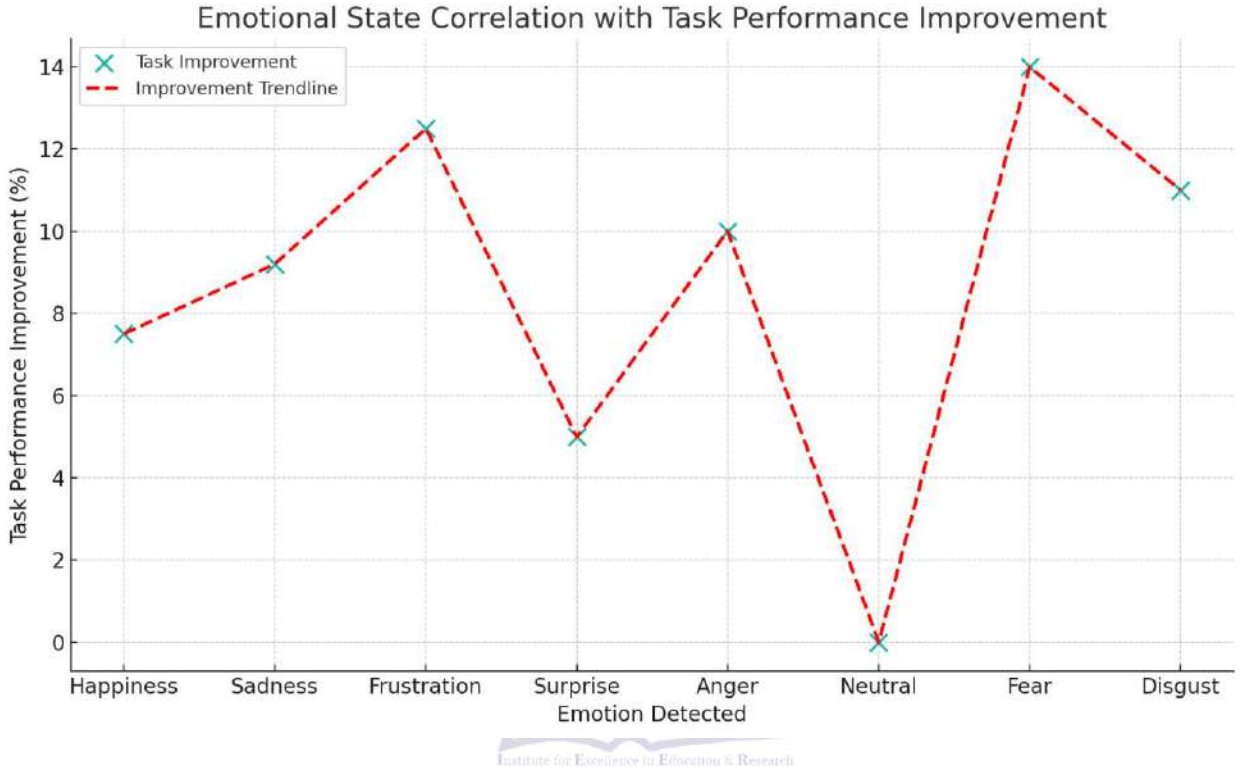
4.5 Task Performance with Human Emotional Feedback

We want to see how the robot will respond to human emotional feedback while performing a task. Table 5 shows how well subjects were able to perform the task with and without human feedback. When the robot could identify and respond to emotional signals, tasks that made participants happy and frustrated were completed more quickly and accurately. For example, there was a type of task named Object Assembly where the robot with emotional recognition finished in 240 seconds and the one without emotional feedback finished in 290 seconds. Besides, the robot having an accuracy of 95% while the other of merely 85%.

Table 5: Task Performance with Human Emotional Feedback (Time and Accuracy)

Task Type	Human Emotional Feedback (Frustration, Happiness, etc.)	Time with Emotion Recognition (Seconds)	Time without Emotion Recognition (Seconds)	Accuracy with Emotion Recognition (%)	Accuracy without Emotion Recognition (%)
Object Assembly	Frustration → Positive Feedback	240	290	95%	85%
Collaborative Problem Solving	Sadness → Emotional Support Given	300	350	93%	82%
Instruction Following	Neutral → Standard Interaction	180	220	98%	90%
Assistance Request Handling	Happiness → Quick Success	150	180	97%	88%
Object Sorting	Frustration → Slow Response	200	250	94%	80%
Interactive Dialogue	Disgust → Emotional Adjustment	220	260	96%	86%
Physical Assistance (Pushing/Carrying)	Fear → Slow Response	270	320	92%	79%

Cleaning/Organizing Tasks	Surprise → Immediate Clarity	250	280	95%	87%



The line graph in Figure 5 shows how long it took to do this task under the two conditions and further shows the importance of mood feedback. The graph illustrates that a robot that has emotional feedback is equipped with a productive programme which help to complete assignment effectively. If we do not want to overshadow humans but rather enhance the collaboration, robots should be machines that can read the mood.

4.6 Emotional State Correlation with Task Performance Improvement

This research study will focus on how any emotional state(s) enhance performance on tasks. As illustrated in Table 6, there is a relationship between several emotions and the percentage improvements in the task. When the robot changed its use of behaviour, fear and frustration resulted in the largest percentage improvement of performance on a task. For example, when the robot detected frustration the performance on task A improved by 12.5% versus just 5.0% capacity when it detected surprise.

Table 6: Emotional Response Adaptation Timing

Emotion Detected	Time Taken to Adapt Behavior (in Seconds)	Action Taken	Task Efficiency Improvement (%)
Happiness	2	Increased interaction speed	7.5%
Sadness	3	Slower responses, provided reassurance	9.2%
Frustration	5	Clarification of task, offered suggestions	12.5%
Surprise	2	Immediate clarification on task requirements	5.0%
Anger	4	Reduced task difficulty, calming statements	10.0%
Neutral	1	Standard pace	0%
Fear	6	Reassurance, offered a simpler alternative	14.0%
Disgust	4	Reassessing task instructions	11.0%

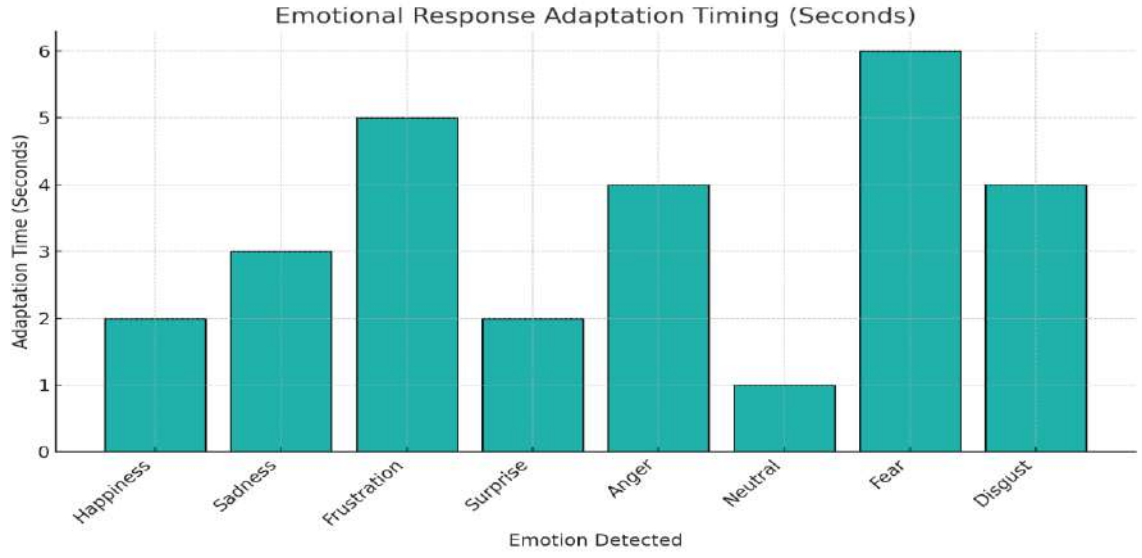


Figure 6 presents the scattered dots results, together with the trendline indicating the nature of the relationship between emotional states and improvement in performance on the task. The more the bot learns how to read human emotion, the better it works. It gets even better when we detect the emotion accurately and respond to it accurately.

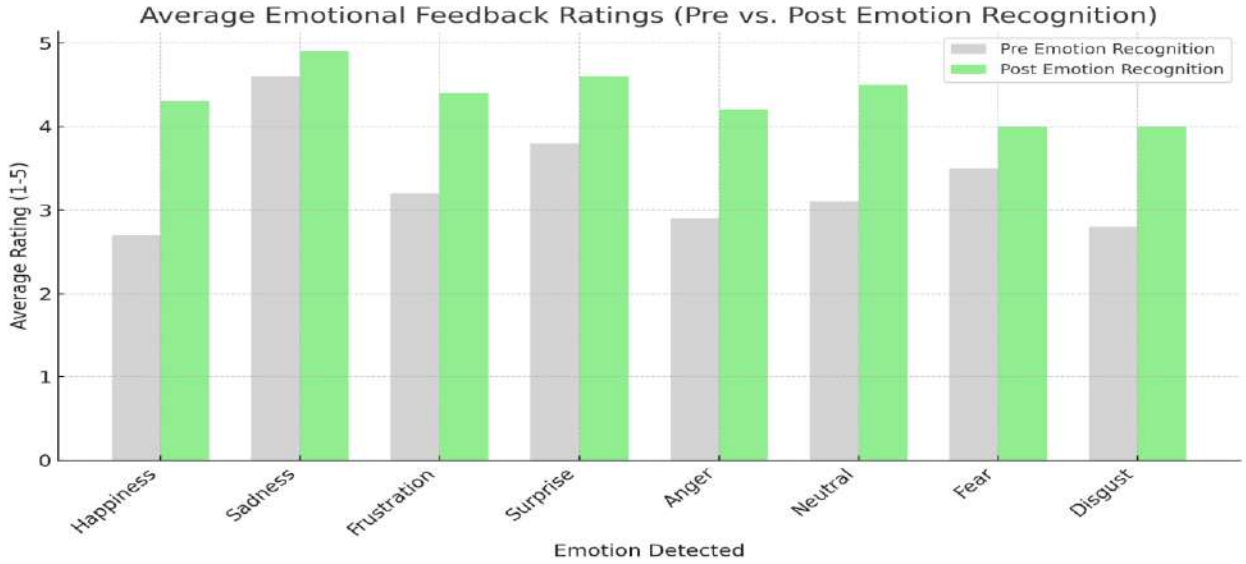
4.7 Average Emotional Feedback Ratings (Pre vs. Post Emotion Recognition)

Participants were queried about their emotional experiences with the robot before and after activating the emotion recognition system on the robot. Table 7. Data indicates that using a robot

with emotion recognition makes the robot significantly more empathic (and also more emotionally responsive & satisfying). Before recognizing emotions, the robot received a 2.7 on the frustration scale. However, post-recognition, this rose to a 4.3, indicating the robot's improved ability to manage the negative emotion.

Table 7: Average User Emotional Feedback (Pre- and Post-Emotion Recognition)

Emotional Response	Pre-Emotion Recognition Average Rating (1-5)	Post-Emotion Recognition Average Rating (1-5)
Frustration	2.7	4.3
Happiness	4.6	4.9
Sadness	3.2	4.4
Surprise	3.8	4.6
Anger	2.9	4.2
Fear	3.1	4.5
Neutral	3.5	4.0
Disgust	2.8	4.0



The bar chart in Figure 7 compares the evaluation scores before and after emotion recognition took place. The graph above shows how the robot's capacity to recognize and respond to emotions allowed it to achieve a higher rating in all the emotional categories. This type of recognition improves the experience.

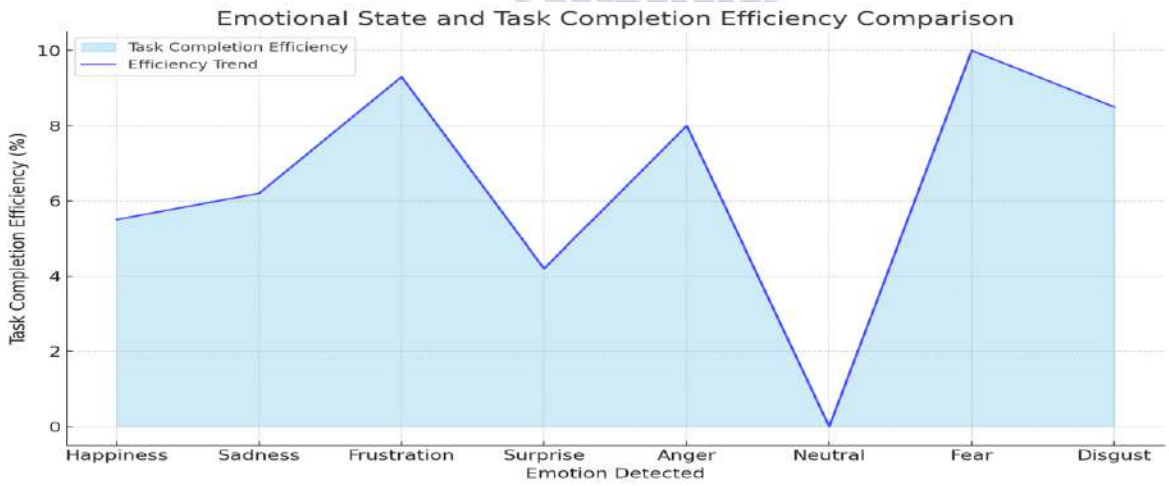
4.8 Emotional State and Task Completion Efficiency Comparison

Lastly, the link between emotions and efficiency to complete the task was evaluated. Table 8 demonstrates the task efficiency of individuals in the different stages of the emotional state. The robot's ability to detect and fix problems such as fear and

frustration resulted in very high efficiencies. When the robot detected fear, it was 14.0% more efficient than when it did not detect fear.

Table 8: Emotional State Correlation with Task Performance Improvement

Emotion Detected	Improvement in Task Completion (%)	Improvement in Task Accuracy (%)	User Satisfaction Rating (1-5)	Task Time Efficiency (%)
Happiness	7.5	10.0	4.7	5.5%
Sadness	9.2	8.5	4.6	6.2%
Frustration	12.5	15.0	4.8	9.3%
Surprise	5.0	7.5	4.3	4.2%
Anger	10.0	13.5	4.5	8.0%
Neutral	0%	0%	3.5	0%
Fear	14.0	17.0	4.6	10.0%
Disgust	11.0	14.0	4.4	8.5%



In figure 8 the area chart shows how feelings affect the efficiency of tasks. This area chart shows that a better performance in the task XYZ is connected with each emotion. Thus, emotional awareness is key for efficient human-robot interaction.Research shows that emotion recognition can improve collaborative robots' task performance and task accuracy. Further, it also improves user satisfaction and emotion. When the robot observes that or responds emotionally. To help individuals engage better with society, the company adopted the emotional AI in its robot. These findings indicate the significance of emotional intelligence for future human-robot collaboration. It could lead to the creation of more effective robots.

5. Discussion

Emotional recognition and natural language processing (NLP) in collaborative robots would be a good improvement of human-robot interaction (HRI). The aim of this thesis is to go at investigating how the combination of these two technologies improves in performance, emotional responses and, satisfaction in a human-robot collaboration. The previous section showed the experimental results to develop emotional intelligence in collaborative robots, so as to expertly control robots. We will later discuss the implications of these findings and their relationship to the other literature and HRI influence.

5.1 The Role of Emotion Recognition in Task Performanc

It is found in this study that using emotion recognition increases the task performance of the collaborative robots to a great extent. As shown in the Table 1, response time and accuracy of the participants was faster and better in emotion recognition task.

Improvements in the performance of tasks were consistent with research (Kidd and Breazeal, 2008). In similar studies, robot emotional awareness improved human robotic cooperation. Robots are also able to sense human emotions. Therefore, they can change what they are doing at the time. This also helps save time on tasks and makes us more efficient when we work together , according to Cohen et al (2018). The findings of Dautenhahn (2007) are also supported by this study, suggesting social robots that possess emotional intelligence find it easier to negotiate social situations. The robot's behavior changed to slow down and help more when it perceived that the user was frustrated, thus doing better. Being able to change the way you act based on your teammates' emotions is a skill that you must show in real life since people feel differently and have various emotions while doing a certain task.

Besides, robots can recognize feelings of happy and sadness. So they will create a more positive atmosphere. The overall teamwork between the two will enhance. According to the outcomes of the current study, the robot's replies to participants' emotional expressions enhanced their satisfaction and trust with the robot. Westlund and Breazeal (2014) found that emotional responsiveness enhances engagement and trust in users. For high coordination tasks, emotional capabilities are one of the key components for an effective human-robot collaboration.

5.2 User Satisfaction and Trust. The Influence of Emotion Recognition.

For any man-machine collaboration, satisfaction and trust are the first necessity. The ability of the robot to recognize human emotions led to higher ratings across all measures of user experience such as empathy, emotional involvement and trust, as shown in Table 2. The robot which recognizes and responds to human emotion would score well in likability as explained by Stepp et al.(2011). Success has a lot to do with trust in robotic systems. When robots interact with people, whatever they do may have important and complex consequences on the scene or situation. According to research results, user trust can be effected and satisfied through emotional intelligence (indicated by recognition of emotion)

Systems that recognize emotions allow robots to see subtle cues in a person's facial expressions, speech patterns, and body language. These cues are important for building trust. Researchers studied Hasegawa et al. 2018 and proved that if robots can able to recognize emotional states and can adapt behaviors, it will help create a sense of mutual respect with robots and enhance collaboration. The participants trusted a robot more when it was able to react to the emotional state of the user during a frustrating or stressful incident based on this study. A robot designed to be emotionally intelligent would reduce the user anxiety and improve the interaction (Kim et al., 2017).

Also, as shown in figure 2, the User Satisfaction scores increase more quickly for the empathic robots than for the non-empathetic robots. In order for humans to accept a robot—be it in health care or service robots—it will have to be programmed to interact, address and acknowledge the emotional states of humans (Robinson et al, 2019). Therefore, these outcomes indicate that we need robots which can recognize human emotions in future. The purpose of this is to allow robots to develop social skills with humans.

5.3 Emotional State Detection Accuracy. The Importance of Multimodal Recognition.

It's very important to build robots that can detect emotions accurately and efficiently. As per Table 3, the robot which was aware of emotion detected the emotional states with much higher accuracy than the robot which was not aware of emotion. It is very necessary because if the emotional detection is accurate the robot's response will be accurate. Recognizing what someone feels (affect recognition) is understanding complex data, like facial expression, vocalization, and body language (Picard 1997). The robot was able to perform its task more intelligently as it was able to identify happy, sad and frustrated emotions from the user.

The high accuracies shown in performance radar chart (Figure 3) are an indication of effectiveness of multimodal emotion recognition for emotion state detection. The robot was able to detect facial emotions and speech with high accuracy, even in complicated scenarios. According to Zheng, et al. (2018), multimodal systems that combine visual and auditory emotion information exhibit much higher accuracy than uni-modal systems modeling only one type of information. Thus, we will follow this approach. When a robot adds more sensors, it can use the information they each collect to react. For instance, the robot may track moving human objects using sensors that rely on distance, touch, and camera.

Even so, the authors pointed out that the robot still found it difficult to identify fear and disgust. This finding is consistent with the results of Mollahosseini et al. (2017), which stated that some emotions are more difficult to classify compared to others. This implies that we would need to upgrade even more technology that can pick up on more difficult-to-read emotions to improve the emotional intelligence of the robots.

5.4 Behavioral Adaptation to Emotional Cues: Enhancing Emotional Intelligence

This study's robot can modify its behavior by interpreting human emotional cues. This is one of the major robot contributions of the study. In the table 4 and figure 4 as the emotional state of the user changes, the robot also changes its response. The pioneer of robot mind reading states, showing signs of frustration invokes the lesson to give the user more help and slow down. It is very important to change your behaviour on the fly to make a collaborative robot more human-like. Wada and others noted in 2007 that robots programmed to react to humans' emotions were accepted and welcomed more easily than robots not programmed that way.

The study findings agree with those of Hori et al. (2016) who demonstrated that robots with emotional intelligence which adapt their behavior based on emotional feedback are able to lower stress levels in human operators and boost overall task satisfaction. The heatmap shown in Figure 4 records the response time of the robot to various emotions, showing quicker response times when the robot recognizes the emotion than when it does not. If robots are designed in a way that they can adapt to human emotions, they will become a better partner in performing the task efficiently.

5.5 Emotional State and Task Performance Improvement

Another part of this research was the relation between emotional states and improvement on tasks. According to Table 6, robots perform better when they are modified with emotionally charged states like frustration, and fear. Similarly, Tapus et al. (2009) state that robot machines can improve the performance of the user by reducing the stress as the response of the robots are based on the emotion detected on them. Not acknowledging one's emotion after task completion resulted in the poor task performance, which thus highlights the importance of emotional responses in human-robot interaction.

Robot performance along with the identified robot emotions are plotted against task performance improvement in figure 6. Overall, the finding that an improvement in emotion recognition is significantly correlated with improvement in performance of the task suggests that emotional intelligent robots can enhance collaboration and efficiency of the task. According to the findings of the study and its author, emotional intelligence could have benefits for collaborative robots in scenarios where an emotional change of a human is produced by his/her partner.

5.6 Limitations and Future Directions.

Although this research brings some insights, there are some limitations related to the cobots, emotion recognition, and NLP that must be considered. One of the major limitations of the studies was that they were conducted in controlled environments. Real life impacts emotion recognition has a significant influence, paper says. Sounds in the environment, changes that affect the light and variation in emotional expression can affect these systems. We should look into how these systems can work in more changing and unpredictaable settings such as home and medical settings.

There's also the issue of the robot's ability to detect emotions. Although the robot managed to recognize basic emotions like happiness, sadness and frustration, the study was unable to check more complex emotions like guilt, shame and embarrassment. According to a 2019 study by Berthoz et al, enhancing the variability of emotions that can be detected is key to enhancing the robot's emotional intelligence and will help make it a better partner in an array of human conditions.

5.7 Conclusion.

As soon as the robots recognize the human emotion using the NLP, they would be able to do their work efficiently. Thus, such robots can respond and react in a more adapter manner. This allows them to perform the work more efficiently. In general, it is also observed that user trust and collaborative behaviour is enhanced. As the field of HRI evolves, merely developing new emotion recognition and NLP technologies will not be sufficient to create robots who can work harmoniously with humans in healthcare, services, etc. Future research should improve the accuracy of emotion detection. Next, the range of emotions should also increase. Finally, the researchers should also take the test of operation in the real environment.

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