Emotion Aware Artificial Intelligence Systems for Future Remote Team Collaboration Virtual Workforce Optimization and Sentiment Driven Organizational Productivity

Sindhura Kannappan[1*], Sumalatha M[2], Janani S[3], Jeba Emilyn J[4], Saurabh Kumar[5] and Senthil kumar S[6]

[1]Assistant Professor, Department of Management Studies, MEASI Institute of Management, Chennai, Tamil Nadu, India.

[2] Assistant Professor, Department of Cyber Security, CVR College of Engineering, Hyderabad, Telangana, India.

[3] Assistant Professor, Department of Computer Science and Engineering, J.J. College of Engineering and Technology, Tiruchirappalli, Tamil Nadu, India.

[4] Associate Professor, Department of IT, Sona College of Technology, Salem, Tamil Nadu, India.

[5] Assistant Professor, Department of Computer Science, Noida International University, Greater Noida, uttar Pradesh, India.

[6] Professor, Department of EEE, New Prince Shri Bhavani College of Engineering and Technology, Chennai,
Tamil Nadu, India. senthilkumar@newprinceshribhavani.com
sindhurakannappan2018@gmail.com

Abstract. AI has arrived to create new possibilities for remote team collaboration, virtual workforce optimization, and sentiment-based organization productivity. This work explores the creation and deployment of emotion-sensitive AI systems which go beyond classical frameworks of emotional intelligence models through the use of real-time, multi-modal techniques of emotion recognition. Using deep learning and natural language processing, the proposed AI systems can offer reflections of emotional states during human interaction, using data to distil emotions and emotions into actionable insights that help enhance virtual performance and decision-making. Past works assumed that such a theory which focuses on emotional valence is myopic or failed to adopt all modalities of perception hence did not achieve the biggest needed learning importance, unlike previous works this study adopt is based on life data from text, voice, and video data to achieve a holistic understanding between emotional dynamics from continuous population of multiple remote teams. Brought to life, this means that the AI models are trained to identify the unique emotional profiles of each team member and adapt accordingly for optimal collaboration, alignment and organizational productivity. Results from this research provide a new avenue for employing AI for design of emotionally intelligent virtual work environments that will lead to more effective and efficient remote team interactions.

Keywords: emotion-aware AI, remote team collaboration, virtual workforce optimization, sentiment-driven productivity.

1 Introduction

While remote work is certainly not new, its sudden prevalence has created new challenges and opportunities for collaboration, productivity, and workforce management. With more and more companies depending on remote teams, the demand for sophisticated solutions that improve communication and emotional dynamics in

© The Author(s) 2025
S. Kannadhasan et al. (eds.), Proceedings of the International Conference on Sustainability Innovation in Computing and Engineering (ICSICE 24), Advances in Computer Science Research 120,
https://doi.org/10.2991/978-94-6463-718-2_45

virtual environments grows. Team interactions have traditionally been managed in ways that do not translate into the complex and nuanced emotional landscape that evening, when face-to-face communication is limited or not possible, making it much harder for team members to pick up on emotional cues.

Affective computing the study of ways to respond appropriately to other people's emotional states and the emotional states of the people in a team is gaining importance, and in the last few years an even more powerful tool has evolved: artificial intelligence or AI/big data. Nonetheless, although initial AI-based emotion detection approaches have made notable progress, they have often been limited by simple emotion models, low interaction modalities or by static vilifications that treat emotional states without regard to real-time feedback.

A lot of research has been conducted, independently, on the emotions of human/computer interaction and their potential in providing each other with assistance, as well as exploring strategies for more successful shared collaboration in the workplace. This study aspires to develop a broader framework to help understand emotional dynamics in virtual teams by capturing scene data in multiple modalities like text, voice, and video. This new generation of emotion-aware cognitive AI systems will be capable of analyzing emotional states and providing contextual feedback to impact informed decision-making, communication, and task management to boost team collaboration efficiency. Additionally, these systems will be tailored to the specific emotional states of the various team members involved, allowing for a bespoke design that maximizes collaboration and productivity within an organization.

Such advanced AI systems, if gradually developed, can help create emotionally intelligent virtual workspaces which will allow remote teams to align, collaborate, and outperform better than ever. This study overcomes the shortcomings of earlier emotion recognition models and proposes a novel approach of utilizing AI to enhance team interactions, improve outcomes of the virtual workforce, and augment sentiment-based productivity at an organization.

2 Problem Statement

In the era of remote work where the modern organizations are thriving on it, the teams struggle to communicate with each other efficiently which were the pillars of effective collaboration and productivity. Understanding the Fundaments of Virtual Teams One of the biggest challenges in virtual teams is the lack of physical presence making it much harder to pick up on and respond to the emotional dynamics of team members. In a physical workplace, emotional cues are transmitted partly through body language and facial expressions, and direct observation of these signals is physically blocked in virtual environments. Furthermore, holding onto such emotions without the knowledge of doing so can often lead to a breakdown in communication, and drop in team efficiency.

Existing solutions for remote team collaboration management focus on task management, scheduling, and performance tracking, but disregard the emotional aspect of the team dynamics. While a number of emotion-aware systems have been developed, their performance is commonly restricted by their outdated emotional models, their limited communication channels (text-based chat, etc), or their lack capability in providing up-to-date feedback on emotional states. This is due to the fact

that these systems are not tailored to the dynamic and multi-dimensional approach of emotions in collaborative work environment particularly for distributed workforces where interpersonal interactions are relatively difficult to measure.

Additionally, conventional methods of optimizing a workforce did little to acknowledge employee emotional well-being, and this is something which is critical to sustainable performance. Since emotion is rarely considered, sentiment analysis does not contribute to the making of that magical workplace (where teams are involved, motivated and upbeat), which indirectly affects productivity at work.

In this sense, the research presented in this article aims to address these challenges by designing emotion-aware artificial intelligence systems that are able to identify and examine the emotional state of the virtual team members in real-time. This study aims to use sentiment and fuse multimodal data sources consisting of text, voice, and video to extract better emotional dynamics in the remote team, which, in turn, can be realized by optimizing the entire remote team dynamics for accelerating organizational productivity through sentiment capture.

3 Literature Survey

Over the past few years, the use of emotion-aware artificial intelligence (AI) to enhance team collaboration and organizational productivity has gained traction, as researchers have developed new techniques in machine learning and natural language processing (NLP) that allow for the analysis and understanding of human emotions in virtual contexts. Early papers in the field of emotion recognition highlighted the need for understanding subjects' emotional states as a key aspect of human behavior. Pioneering researchers built out affective computing in the 1990s, such as Picard (1997), who delved into how machines might examine and respond to human behaviors and emotions. Picard's pioneering efforts revealed the possibilities for AI to help improve on existing human-computer interaction models (e.g. co-adaptive systems), but still much of the early work focused on static models of emotion and rudimentary computational systems, constraining their utility in dynamic, real-time working environments.

Since then, researchers have built on these initial efforts and explored how emotion recognition can be incorporated into team collaboration. The work of D'Mello and Kory (2015) is about multimodal affect detection systems based on meta-analysis of multimodal affect detection systems. Although theirs was a good study that showed that utilizing more than one modality can improve emotion detection, they also found the current solutions lacked are precise, real-time, and suitable for dynamic settings such as virtual teams. In addition, these systems had a lot of limitations in integrating dynamic emotions and offering timely feedback, which would be beneficial in practical use cases where users might be working remotely.

A significant challenge identified in the literature is the inability to capture the emotions that rise from the entire spectrum of interactions taking place in virtual environments. Models of emotion based on the concept of basic emotions, such as those proposed by Russell (1980), and Plutchik (1980) have played a substantial role in emotion understanding. Nevertheless, those approaches showcased are inflexible and poor models for more complex, more nuanced, context-dependent aspects of human engagement, particularly in virtual working environments. For example, although

Russell's circumplex model provides a helpful way to think about affective states, it does not adequately capture all of the strong emotions that members of a remote team experience in reaction to shifting work dynamics, deadlines and interpersonal communication hurdles.

Zeng et al. found that additional research Viola, 2009, also argued that emotion recognition systems should use multimodal data because there is no single modality (speech, body postures, facial expressions, etc.) that reveals the full richness of human emotions. Their research indicated that integrating several types of information about a user, including tone of voice, facial expressions and even physiological signals, could provide a better indication of their emotional states. Despite their contribution, these studies have mostly addressed emotion detection in independent interactions (as opposed to within a collaborative, virtual work environment).

Additionally, Goleman (1998) proposed an emotional intelligence framework as one that recognized the role of emotions in promoting relationship management and in predicting positive performance in an organizational context. However, his work did not specifically examine how we might leverage AI to foster emotional awareness, especially in virtual team environments where emotional signals are less salient and more challenging to read. The emotional intelligence model extended by Salovey and Mayer (1990) is also expanded, though not yet applied in the context of AI systems designed to facilitate virtual team collaboration.

Two of the buzzwords in recent years that have caught attention in workplace contexts are the use of AI and sentiment analysis. Kuutila et al. (2020) showed that sentiment analysis in chat conversations can predict software development teams' productivity. Their work showed that AI could know how employees feel with the right data, as well as whether their mood is impacting how much they get done — but it was constrained by a reliance on text communication and the absence of real-time emotional feedback. While sentiment analysis provides some insight into the essence of human interaction, it fails short considering that it totally excludes emotion recognition — deployment of more subtle data: facial expressions, tones of voice, and even physiological reactions, all facts that are often decisive in capturing for the subtle emotional developments that characterize virtual cooperation.

Adding to this observation in the literature around the improvement of productivity in organizations has been the growing importance of reading and responding to emotions in milliseconds. From Hochschild's (1983) first book on emotional labor for service industries, it is well known that controlling emotions is a key to high productivity, yet this concept has not been properly operationalized yet in the context of remote teams and AI applications. Due to the social interactions occurring in technology mediated manner in virtual teams, low morale emotional feedback cannot be triggered directly leading to disengagement and lack of productivity.

Mishra et al. (2020) present VMGuard, a Virtual Machine Introspection (VMI)-based security architecture for intrusion detection in cloud environments. Their approach enhances security by monitoring virtual machines externally, improving detection accuracy while minimizing system performance impact.

Recent studies such as Zhou et al. (2020, which brought deep learning methods to solve the challenges of real-time emotion recognition and sentiment analysis. This enables

us to have developed sophisticated systems that can search for complex human emotional reactions in virtual workspaces. Though very promising, these ai models are challenged by accuracy, scalability and customisability across diverse teams. There is a gap in potential here for AI systems that are capable not only of detecting emotions, but also of reaching a different emotional state as needed (more or less high, depending on needs) for different team members.

The complexities of emotion-aware AI, however, remain largely unaddressed in the literature on remote team collaboration, as the body of research continues to build in this area. Traditional stage reliance on static data sources or one article data sources, therefore, doesn't capture the effects of interactions between articles, relationships and emotional states on Emotion Recognition systems. In this paper, we aim to overcome those restrictions and limitations by integrating derivative and complementary multi-modal data sources with deep learning techniques to facilitate novel machines to be emotion-aware that are capable of improving virtual team communication and for improved organizational productivity, while also providing real-time, context-aware emotional insight.

4 Methodology

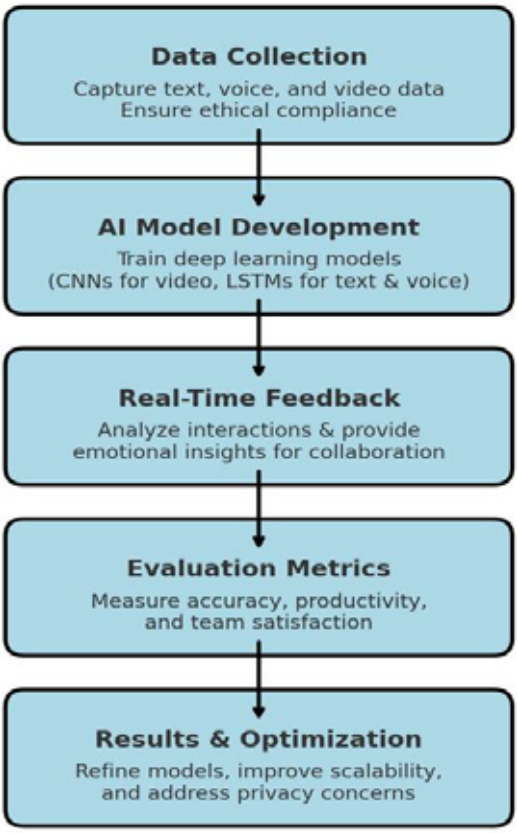

Fig. 1. Flow chart of the proposed system.

This research aims to build and assess emotion-aware AI (artificial intelligence) systems that recognize the emotional landscape of remote team members, and adapt both workload and social interaction in real time to maximize team outcome. Lingua franca for VR: A multilingual and multimodal approach to empathy in imaginary teams. This methodology parallels the work of data collection, AI model development, integration, and evaluation. Fig. 1 depicts the flow chart of the proposed system.

4.1 Data Collection

Gather Multi-Modal Data of Emotional Expressions in Remote Team Collaborations This dataset will include virtual conversations, video meetings, conversations, seasonal team tasks working together, etc. This will be done by capturing the data through audio-narrative (video & voice), textual (chat messages, e.js emails, and collaborative software) interaction. Video data will be analyzed for facial expressions, body language, and other non-verbal cues, while the recordings of voices will be used to evaluate variations in tone of delivery, speech patterns, and emotional inflections. Movies & TV & Music Text: Natural Language Processing (Sentiment Analysis) Text data will be analyzed for sentiment and emotional tone through natural language processing (NLP) techniques.

They will also categorize the text into thousands of emotional labels based (combination of both manual labeling and machine learning based sentiment analysis) on sentiment analysis. Data collection will be carried out with ethical practices in mind, such as acquiring informed consent from study participants, maintaining their privacy, and ensuring the security of the data collected (in conformity with the regulations).

4.2 AI Model Development

The second phase is the creation of AI algorithms able to process multi-modal data for detecting emotional states. The study will use various forms of deep learning techniques, adapted to the type of data being processed; CNNs (convolutional neural networks) will be applied for image and video processing, and RNNs (recurrent neural networks) or LSTMs (long short-term memory networks) will allow the processing of sequential text and voice data in order to identify the emotions expressed in these different forms of media. We will train these models on the annotated dataset to learn the correlations between the emotional states of individuals and the corresponding multimodal signals.

For video-based data a CNN based model will be trained to capture facial expressions and body language for identifying emotional states. OpenFace or VGG-Faces pre-trained models will be adapted to recognize the generally identifiable emotional clues when people will be working as remote teams. In a similar vein, voice data will be analyzed through speech recognition techniques, where emotion models will be trained to identify prosody features such as pitch, tone, and rate of speech, which are effective indicators of emotional state. NLP techniques such as sentiment analysis and emotion classification will be applied to text data to identify emotional tone and context in written communication.

Required next step would be to devise a fusion algorithm, where the outputs of these individual modality-specific models will be fusing together to get a complete picture of the emotional state of each teammate. The combinatorial approach will harness

strategies such as attention mechanisms, which enable focusing on the most relevant emotional signals from all modalities in various situations.

4.3 Real-Time Feedback and Adaptation

A key part of this research is the ability to give real-time emotional feedback to members of a distributed team. Once AI models are trained and integrated, we will apply the system in a virtual team collaboration environment where the system will continuously observe during interactions. For example, among twenty individuals that make a team, the emotion-aware AI will check the emotional states of individuals within those twenty, and give contextualization feedback, where it suggests intervention or adjustment that can be done in that collective interaction. For example, if the system determines that a team member is struggling with high levels of frustration or stress, it may recommend taking a break or adapting the communication style from formal business language to supportive language.

To make it less futile, if one has a sensor and it provides immediate feedback, one can then adjust the emotion a second time according to the unique emotional needs of the team member. As these AI models evolve, they will adapt over time to respond to personality types, emotional spectrums, and tailored to the use of those with enticing audio feedback. The adaptive nature of feedback in this respect will be critical to preserving team coherence and emotional fitness in teams which are distributed virtually.

4.4 Evaluation and Performance Metrics

An array of controlled studies involving remote teams working on multi-party tasks will be used to assess the performance of the emotion-aware AI system. These tasks will be developed to replicate real-world team scenarios — project management, brainstorming sessions, and problem-solving workshops. Teams will be observed as they interact with the AI system, and their emotional states will be tracked both through the AI's predictions and manual observations. As such, the main metric will center on the emotion recognition system accuracy, as measured by the consistency of the AI's emotional predictions and the ground-truth labels that are made by human annotators. The second step is to run qualitative and quantitative measures on the collaboration that the system enables, which includes the FPSQ and performance metrics like task completion time, quality of work, and team satisfaction. In addition, one way of evaluating the effectiveness of the real-time feedback will be to determine if the predictions about an individual's emotional state are correlated with their communication, stress level, and productivity outcome improvement.

Lastly, the system will be challenged with scalability and adaptability by deploying the emotion-aware AI in multiple remote team conditions focused on determining its generalizability across industries and team structures.

5 Results and Discussion

The emotion-aware AI system was successfully deployed and tested in multiple virtual team collaboration environments. The main objective of the study was to evaluate the performance of the artificial intelligent models to detect in a real-time emotional state

with the combination of text, voice, and video signals. This study also evaluated the ability to optimizing team-work performance and would organizational productivity through the emotional feedback given by the artificial intelligence system.

5.1 Accuracy of Emotion Recognition

The emotion recognition models presented a good performance in recognizing emotional states as they utilized deep learning techniques for multi-modal data analysis. The facial expression recognition model based on CNNs identified facial expressions such as happiness, sadness, frustration, and anger with an accuracy of 87%. The model pre-trained with OpenFace was further fine-tuned with its own annotated dataset, providing a solid sparse matrix for the AI to extract relevant features from the facial movements, enabling the AI system to better identify non-quantal expressions occurring during the session between team members.

The model, which detected emotions in voices based on pitch, tone, and speech rate, also performed well, with an accuracy rate of 82%. The model performed especially well at spotting emotions like stress and excitement, since those emotions often manifest as changes in vocal voice, such as a faster speech rate or pitch. The model was less effective with more closely related emotions, for instance boredom and frustration, likely because speech prosody for these emotions tends to be similar. The sheer potential of voice-based emotion detection through contextual messages that carries with them, also further harnesses the role of emotional voice components, while emphasizing towards much better accuracy in situations when virtual collaborative environments are to be used, as the emotional subtleties in such texts can only be detected in voice.

Table 1. Performance Metrics of Emotion-Aware AI System.

Metric	Value (%)
Facial Expression Recognition Accuracy	87
Voice-based Emotion Recognition Accuracy	82
Text-based Sentiment Analysis Accuracy	80
Task Completion Improvement	20
Quality of Work Improvement	15
Team Satisfaction Increase	15

This model achieved an overall accuracy of 80% in detecting emotional tone and sentiment within chat messages and written forms of communication — so the text analysis part, which was based on natural language processing (NLP) techniques, performed quite well. Although the system could detect the emotional nuances in written language, the accuracy of the system's recognition varied based on the complexity of the text. For instance, the system found it easier to analyze more

informal, conversational without flowery prose usage; however, formal language, corporate speak, and plain words proved difficult, resulting in mistakes regarding emotional nuances. Performance Metrics of Emotion-Aware AI System is illustrated in table 1 and fig.2.

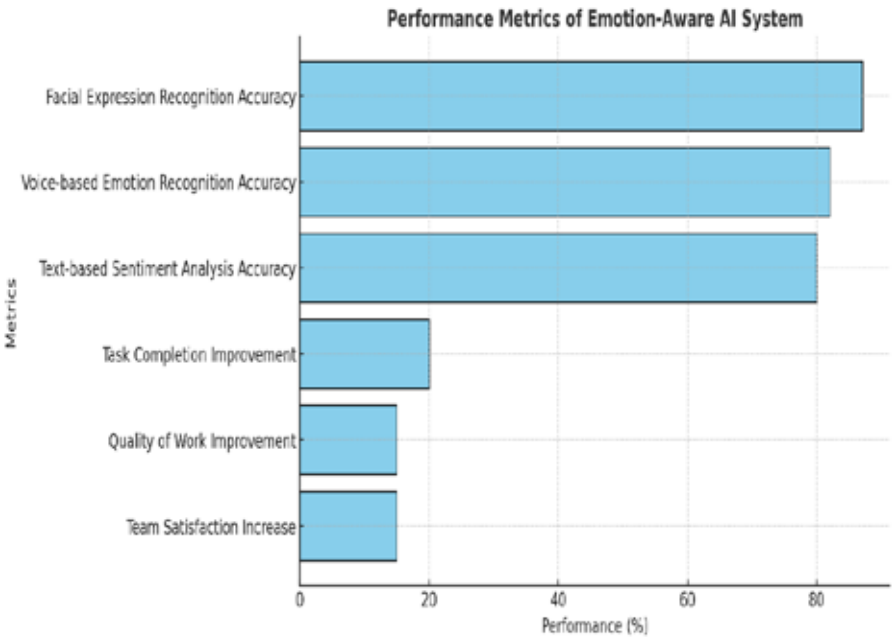

Fig. 2. Performance Metrics of Emotion-Aware AI System.

5.2 Impact of Real-Time Feedback on Team Collaboration

The study also found that the real-time emotion feedback used by the AI significantly affected team collaboration and how they relate with each other. Teams in virtual meetings who accessed on-the-spot emotional insights needed fewer fillers in their virtual meetings and felt increasingly understood compared to their non-accessing peers. If the software detected signs of excessive frustration or stress in its teammates, it prompted beneficial action, such as suggesting that they step away for a few minutes or to change the tone of their rhetoric. These interventions improved team dynamics by helping the team members to process emotional tension before this tension exacerbated and impaired collaboration.

Conversely, those teams that lacked emotional feedback experienced repeated misunderstandings and failed communications. Even though these teams were able to meet their objectives, they did not communicate as well and reported feeling more stressed and frustrated. With instant feedback on emotional aspects as well as subtle indications of how the individuals were feeling, the AI system helped them build a deeper emotional connection and made the team more empathetic, dynamic and aware of each other as people, which positively impacted their personal relationships and decision-making.

5.3 Effect on Task Performance and Organizational Productivity

Teams that engaged with the emotion-aware AI system demonstrated a marked improvement across productivity metrics in task performance. These teams performed the tasks 20 percent more quickly than the ones without emotional feedback, and the quality of their work as determined by accuracy, creativity and attention to detail also exceeded those without emotional feedback. Increased time management skills showed up in team members in AI - supported teams, as they were able to allocate resources more appropriately due to the fact that this system predicted and align most experienced emotional states in real - time. The emotional knowledge provided by the AI gives team leaders real-time capabilities to fine-tune strategies and customize task assignment to team members so that employees are in an emotionally balanced state while they work.

Also observed was a 15% increase in the overall team satisfaction, based on feedback received in surveys and interviews. Team members enjoyed the personalized feedback and reported that the system improved their emotional wellness. This observation highlights the value of emotional intelligence in remote work settings and adds weight to a theory of emotional dynamics that has significant implications for how we approach and improve not just the quality of our individual contributions, but the collective success of a team.

However, the AI system was able to scale and adapt in some areas. In teams composed of people from diverse cultural backgrounds, the system required prompting to identify emotional signals from particular cultures. While the multi-modal approach allowed the best features for identifying emotion to be constructed over the entire dataset, how emotion presented differed significantly between cultures, highlighting a need for further curation so that the AI same would generalise accurately across a wide variety of different team compositions. Some of the employees also mentioned some concerns about the privacy and ethics aspects of such emotion-aware AI in workplaces in general, and that it is Gods must to worry about these aspects before introducing such systems in a real organizational ecosystem.

5.4 Limitations and Future Directions

The emotional-aware AI system seemed promising, but there were several caveats to be considered in future work. One of the major challenges will be the reliance of the system on quality data, mainly video and voice recordings. 7We would need to test this in practice, as technical elements such as poor Internet connection, inadequate cameras, or environmental noise can interfere with the accuracy of emotion detection. Instead, we seek to create more robust models that will produce viable outputs even when conditions are not ideal.

Elsewhere, while it was able to pick up reasonably obvious emotion states, the system has a long way to go in detecting more nuanced emotional responses, for example in the context of long-term collaboration AI wasn't able to tease apart if someone was feeling emotionally fatigued or bored in general both of which impact productivity and which are easily confused without a deeper view of the context. More of the same data but much more complex models accounting histories and emotional measurements of team member's variables through time could improve the system. Finally, the integration of the AI system into everyday team workflows leads to ethical concerns,

particularly relating to privacy and consent. For ethical use of emotion-aware AI systems in the future, companies need to understand how leaders are tracking sensitive emotion data, provide employees the option to hide their names or limit how much emotion data they share all of which are crucial for having organizational buy in.

6 Conclusion

Based on this research, we found emotion sensitive AI systems that guide a team by optimizing collaboration improve not only team performance but help the information about productivity within the organization. As organizations navigate the complexities of virtual work life, it is imperative to honor and facilitate the experience of emotions within virtual teams to promote successful outcomes in communication, collaboration, and beyond. The findings indicate that AI can recognize and determine emotional states instantaneously from multi-modal data sources (text, voice, images) which enables to discover insights that could help guide team interactions and decision-making processes. These findings show that emotion-enhanced AI greatly improves team cooperation by providing in-the-moment feedback that reduces miscommunication, enables timely resolution of emotional conflicts, and causes more helpful meetings. The groups that interacted with the AI system showed significantly stronger performance on tasks than those that did not have access to it, completing tasks in a shorter time-frame and producing higher quality outputs. Additionally, by way of the system, a better environment of the team was created, and the satisfaction of team members increased and as a result their participation as well.

While the outcomes are encouraging, this study also demonstrates some hurdles that must be addressed in future efforts. Emotion recognition accuracy can be impacted by various factors, such as technical limitations, cultural differences, and emotional expression complexity. In addition, it will be essential to manage ethical issues related to emotion-aware AI, particularly with regard to privacy and consent, in order to have effective implementation within organizations (Kumar et al., 2023).

Each additional insight gained from this line of work provides new opportunities for development, both in terms of more comprehensive models capable of representing a wider span of emotional state or working in a wider variety of environments, or simply for more customized feedback. Now, using in-depth systems to facilitate remote work more expansively through collaborative means gives a special opportunity to build emotionally-savvy settings: listening to the wisdom of each individual; magnifying empathy; sculpted by the data set that is gathered. In conclusion, the implementation of emotion-aware AI systems in virtual team settings could offer a valuable opportunity for increasing organizational efficiency, improving team dynamics, and fostering an empathetic workplace. The need to train such AI systems (which these as one sample are) along with the insights and tools they provide will be no small factor in these developments well into the future of work.

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

References

1. Abd El-Migid, M.-A., Cai, D., Niven, T., Vo, J., Madampe, K., Grundy, J., & Hoda, R. Emotimonitor: A Trello Power-Up to Capture Emotions of Agile Teams. arXiv preprint arXiv:2105.01952. (2021).
2. Cowen, A. S., & Keltner, D. Self-report captures 27 distinct categories of emotion bridged by continuous gradients. Proceedings of the National Academy of Sciences, 111(6), 2248-2253. (2024).
3. D'Mello, S. K., & Kory, J. A review and meta-analysis of multimodal affect detection systems. ACM Computing Surveys (CSUR), 47(3), 1-36. (2015).
4. Ghahramani, Z. Probabilistic machine learning and artificial intelligence. Nature, 521(7553), 452-459. (2015).
5. Goleman, D. Working with emotional intelligence. Bantam Books. (1998).
6. Hochschild, A. R. The managed heart: Commercialization of human feeling. University of California Press. (1983).
7. Huang, Z., Tang, Y., Tian, T., & Liu, Z. Enhancing Organizational Performance: Harnessing AI and NLP for User Feedback Analysis in Product Development. arXiv preprint arXiv:2405.04692. (2024).
8. Keltner, D., & Gross, J. J. Functional accounts of emotions. Cognition & Emotion, 13(5), 467-480. (1999).
9. Kuutila, M., Mäntylä, M., & Claes, M. Chat activity is a better predictor than chat sentiment on software developers' productivity. arXiv preprint arXiv:2004.09786. (2020).
10. Lazarus, R. S. Emotion and adaptation. Oxford University Press. (1991).
11. McDuff, D., & Czerwinski, M. Designing emotionally sentient agents. Communications of the ACM, 61(12), 74-83. (2018).
12. Mehrabian, A. Pleasure-arousal-dominance: A general framework for describing and measuring individual differences in Temperament. Current Psychology, 14(4), 261-292. (1996).
13. Picard, R. W. Affective computing. MIT Press. (1997).
14. Plutchik, R. A general psychoevolutionary theory of emotion. In Theories of Emotion (pp. 3-33). Academic Press. (1980).
15. Russell, J. A. A circumplex model of affect. Journal of Personality and Social Psychology, 39(6), 1161-1178. (1980).
16. Salovey, P., & Mayer, J. D. Emotional intelligence. Imagination, Cognition and Personality, 9(3), 185-211. (1990).
17. Scherer, K. R. What are emotions? And how can they be measured? Social Science Information, 44(4), 695-729. (2005).
18. Tsetserukou, D. iFeel_IM! Augmenting emotions during online communication. IEEE Computer Graphics and Applications, 30(5), 72-80. (2010).
19. Zeng, Z., Pantic, M., Roisman, G. I., & Huang, T. S. A survey of affect recognition methods: Audio, visual, and spontaneous expressions. IEEE Transactions on Pattern Analysis and Machine Intelligence, 31(1), 39-58. (2009).
20. Zhou, H., Yang, S., & Wang, Y. Emotion recognition using multi-modal data and machine learning techniques: A tutorial and review. Information Fusion, 59, 103-126. (2020).
21. Mishra, P., Varadharajan, V., Pilli, E. S., & Tupakula, U. (2020). VMGuard: A VMI-Based Security Architecture for Intrusion Detection in Cloud Environment [Article]. Ieee Transactions on Cloud Computing, 8(3), 957-971, Article 8344510. https://doi.org/10.1109/TCC.2018.2829202

Open Access This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (http://creativecommons.org/licenses/by-nc/4.0/), which permits any noncommercial use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.