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International Journal of Combinatorial Optimization Problems and Informatics, 17(3), 2026, 146-165. ISSN: 2007-1558. https://doi.org/10.61467/2007.1558.2026.v17i3.1398

Emotional AI in the Workplace: Systematic Review of Effects on Employee Well-Being, Productivity, and Organizational Performance

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Abstract. The rapid integration of Artificial Intelligence (AI) and affective computing technologies into organisational environments is transforming workplace dynamics. However, their impact on employee well-being and productivity remains fragmented and insufficiently synthesised. This study addresses this research gap through a systematic review of AI-powered emotional intelligence systems. It focuses on their effects across three core dimensions: employee attitudes (job satisfaction, motivation, adaptability), workplace behaviours (performance, creativity, technology adoption), and organisational dynamics (leadership, trust, team cohesion). Following the PRISMA framework, this study conducts a systematic evaluation and comparative analysis of the state-of-the-art literature. It identifies key patterns, methodological trends, and underexplored areas. The findings suggest that emotional AI systems may enhance employee engagement and organisational productivity when implemented within ethically grounded and transparent frameworks. However, the review also highlights critical challenges related to privacy, emotional surveillance, algorithmic bias, and employee trust. This study contributes a structured framework that clarifies the role of emotional AI in organisational contexts and outlines actionable, scalable strategies for real-world application. By consolidating dispersed evidence and proposing directions for future research, this study is intended to provide a benchmark for subsequent investigations into AI-driven emotional intelligence and its implications for sustainable, human-centred workplaces.

Keywords: Emotional Artificial Intelligence, Affective Computing, Employee Well-Being, Organizational Productivity, Workplace Analytics, Human–AI Interaction, Algorithmic Bias and Ethics, Digital Transformation in Organizations.

Article Info
Received Dec 26, 2025
Accepted April 11, 2026

1 Introduction

Emotional Artificial Intelligence represents a significant milestone in the integration of advanced technology with the understanding of human emotions. This field involves methodologies aimed at identifying and interpreting emotional states through the analysis of diverse data inputs such as facial expressions, voice modulations, and physiological signals. Significant progress has been achieved, particularly through the application of deep learning algorithms, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs). These techniques are well suited to capturing both local and dynamic features inherent in emotional data and have demonstrated strong performance across applications. A notable example is the BiLSTM–Transformer architecture combined with 2D CNNs, which has been reported to achieve high accuracy in recognising emotions from speech, suggesting its potential to enhance human–computer interaction (Kim and Lee, 2023; Hong, 2020). The theoretical underpinnings of this domain can be traced to the work of Darwin and Ekman, who established the universality of emotional expressions across cultures, providing a foundation for developing robust methodologies in emotional AI (Xu, 2024).

The versatility of emotional AI is evident in its integration across various sectors, including healthcare, marketing, and education. In healthcare, emotion recognition systems can facilitate the monitoring of patients' emotional states, potentially fostering improved therapeutic relationships and adherence to treatment plans (Yang et al., 2022). Similarly, in marketing, the ability to analyse consumers' emotions may enable companies to design targeted strategies aimed at audience engagement and retention (Huang and Rust, 2020). Education also may benefit from these technologies through emotionally adaptive learning systems that enhance student engagement. These applications illustrate the practical relevance of emotional AI, bridging technical innovation with societal needs. Despite its advantages, however, emotional AI introduces ethical and practical challenges, particularly regarding its implementation in organisational settings.

The workplace represents a critical area for the application of emotional AI due to its potential to transform organisational dynamics, employee productivity, and overall well-being. By leveraging tools that analyse facial expressions, vocal patterns, and other behavioural data, organisations may adapt their management strategies to align with employees' emotional needs. This may foster greater affective engagement, which is considered an important factor in improving job performance and reducing employee turnover (Febrianti, 2023). Furthermore, emotional AI can assist in detecting signs of stress or disengagement, enabling managers to intervene and promote a supportive work environment. However, these benefits are not without complications. Employees may perceive such monitoring systems as intrusive, particularly when emotional surveillance practices are introduced without transparent communication or ethical safeguards (Roemmich, 2023).

The ethical challenges associated with emotional AI in the workplace are substantial and multifaceted. Concerns primarily revolve around privacy and the use of emotional data, as employees may view such technologies as a violation of personal boundaries. Studies indicate that discomfort stemming from emotional monitoring in professional settings can disrupt contextual norms regarding emotional expression (Roemmich, 2023). Moreover, these tools may exacerbate emotional labour demands, imposing psychological costs on employees required to manage their emotions in response to AI-driven evaluations (Roemmich, 2023). Addressing these issues is likely to require the establishment of clear international standards and ethical guidelines to regulate the collection, analysis, and application of emotional data.

The absence of comprehensive ethical and regulatory frameworks further complicates the adoption of emotional AI technologies. As organisations increasingly implement these systems, discrepancies in cultural perceptions and regulatory approaches have emerged. For instance, some cultures may view emotional surveillance more favourably, whereas others may perceive it as intrusive and counterproductive. These disparities may hinder widespread acceptance and highlight the need for globally consistent guidelines that safeguard employee privacy while optimising the benefits of emotional AI (Mantello et al., 2021). Without such measures, organisations risk alienating their workforce and compromising the efficacy of these technologies. To address these gaps, this article emphasises the importance of considering interdisciplinary collaboration in developing ethical frameworks that account for diverse cultural contexts and organisational structures.

This article synthesises critical findings from existing research on AI-based emotional intelligence systems, focusing on their influence on employee well-being and organisational productivity. By systematically reviewing empirical studies, it identifies patterns, trends, and research gaps, highlighting the dual potential of emotional AI to enhance workplace engagement while introducing ethical challenges. To ensure sustainable adoption, organisations are encouraged to prioritise strategies that balance technological innovation with human-centred principles. Recommendations include the integration of robust privacy measures, transparent communication practices, and tailored interventions to address cultural and organisational differences. These measures may support the optimisation of emotional AI implementation while fostering workplaces that prioritise well-being and productivity.

A range of theories regarding Emotional Intelligence (EI) and human behaviour are employed in this research to establish a robust conceptual framework. According to the Mayer–Salovey–Caruso model, EI is generally understood as the ability to perceive, interpret, and manage emotions. In another model, Goleman emphasises EI as a set of skills necessary for leadership, empathy, and effective social functioning. In addition, the Job Demands–Resources model explains how employee engagement or burnout is linked to job demands and resources. By linking these theories to the use of AI in emotional intelligence, the research examines how technology may emulate or amplify human emotional capabilities. A combination of these theoretical perspectives may assist in understanding how AI influences emotional dimensions across different workplace contexts.

2 Methodology

The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework was applied to ensure a rigorous and transparent approach in this systematic review. Systematic reviews and meta-analyses have gained prominence across various fields due to their ability to synthesize vast amounts of data into meaningful insights. The field of Artificial Intelligence, particularly in emotional intelligence systems, has witnessed rapid advancements in models, algorithms, and applications across di- verse sectors. For example, the medical field has seen continuous updates driven by the unique characteristics of individual cases, necessitating detailed reviews to aid in decision-making (Swingler et al., 2003). Institutions such as the Canadian Institutes of Health Research (CIHR) have highlighted the value of systematic reviews in promoting innovation and guiding evidence-based practices. The clarity, reproducibility, and depth provided by the PRISMA methodology make it particularly suitable for synthesizing the impact of AI-based emotional intelligence systems on employee well-being and organizational productivity.

Detailed PICO Framework

To simplify the research plan, here is a basic breakdown of the PICO framework: Population (P): Workers in companies that have adopted AI-powered emotional intelligence systems; Intervention (I)—Using AI tools to identify and respond to employees' emotions; Comparison (C) corporations that use traditional methods to assess employee happiness and performance without using artificial intelligence; Outcome (O) better emotional health; higher job satisfaction; more engaged workers; improved productivity; and stronger teamwork. The PICO structure is thorough and provides a detailed account of the study's focus, while also adhering to standard research review techniques

To ensure relevance and rigor, inclusion and exclusion criteria were clearly defined. The inclusion criteria focused on empirical studies conducted in organizational contexts that reported on the impacts of AI on employee well-being or productivity. Only articles published in English, designed with empirical methodologies, and indexed in reputable databases between 2013 and 2023 were considered. Exclusion criteria included theoretical studies lacking empirical evidence, research conducted outside workplace settings, and non-peer-reviewed publications. This selection process aimed to prioritize robust data and actionable insights. By refining these criteria, the review targeted studies that align with the overarching goal of understanding how AI-based emotional intelligence systems compare to traditional approaches in improving workplace outcomes.

The research question was structured using the PICO (Population, Intervention, Comparison, and Outcomes) framework, which provides a systematic method for defining key components of a study. The population included workers from organizations implementing AI-based emotional intelligence systems, while the intervention involved the deployment of these technologies to enhance emotional intelligence in workplace settings. Comparisons were drawn between organizations with and without such systems, focusing on outcomes like employee well-being and organizational productivity. The guiding research question was thus defined as: How do AI-based emotional intelligence systems support employees compared to traditional methods for monitoring well-being and productivity? This structured approach ensured alignment with the study objectives and relevance to the broader research landscape.

The evidence acquisition process included a comprehensive bibliographic search across databases such as Scopus, Web of Science, and Google Scholar. Specific search terms, including AI-Powered Emotional Intelligence Systems Impact on Employee Well-Being and Organizational Productivity, AI emotional intelligence, and AI workplace, were iteratively refined to ensure the retrieval of relevant studies. The search process was conducted in three stages: (1) screening abstracts from gray literature, which initially yielded 1,200 articles; (2) eliminating 200 duplicate entries; and (3) reviewing the full texts of 400 studies, from which 46 were selected for the final analysis based on relevance and quality. This multi-step process ensured a rigorous and focused synthesis of the available evidence.

The PRISMA methodology facilitated the systematic synthesis of findings, emphasizing transparency and replicability. The initial search identified a diverse range of studies, which were then filtered through the inclusion and exclusion criteria. Studies were categorized by their relevance to the research question, methodological rigor, and reported outcomes. The systematic approach enabled the identification of gaps in existing research, providing a foundation for future studies. By focusing on both the empirical and practical applications of AI-based emotional intelligence systems, this review not only highlights their potential benefits but also addresses ethical, organizational, and contextual challenges.

The data extraction process plays a pivotal role in systematically organizing and analyzing the collected evidence, ensuring uniformity and coherence. To this end, the data extraction form incorporates carefully selected items designed to capture essential aspects of each study. These include the type of study—whether qualitative or quantitative—the methodological framework, and the specific AI-based emotional intelligence (AI-EI) technologies applied. Furthermore, the indicators of impact, such as employee well-being and organizational productivity, are integral to evaluating the outcomes of these technologies. Additional attention is given to participant demographics and the metrics used to measure results. This structured approach facilitates the identification of trends, comparison across studies, and a comprehensive understanding of key impact areas. Such a methodical strategy provides a robust basis for synthesizing findings and deriving actionable insights (Kim & Lee, 2023).

Confounding parameters are one of the most critical threats to the validity of research findings, and addressing them is crucial to ensure reliable conclusions. This review identified three primary parameters: the nature of the study, the mandatory use of AI, and the indicators of human quality impact. The nature of the study examines whether the research employs experimental or descriptive designs, as this distinction can significantly influence interpretations. Ensuring the mandatory use of AI aligns each study with the review's objectives, guaranteeing relevance. Finally, human quality indicators, including job satisfaction, team cohesion, and mental health, serve as benchmarks for evaluating the transformative potential of AI-EI systems. By systematically addressing these parameters, the review minimizes bias and strengthens its findings (Hong, 2020).

The classification of studies was another cornerstone of this review, providing a structured method to organize diverse research findings. The classification table grouped studies based on several criteria: the type of AI technology utilized, measured outcomes, and the context of application. For instance, studies employing CNNs for emotion recognition were distinguished from those utilizing generative models like GPT for empathetic communication. Methodological details such as sample size, experimental design, and data sources were also included, allowing for nuanced comparisons and clearer insights. Moreover, this categorization revealed gaps in the literature, particularly in areas such as longitudinal impacts of AI-EI on organizational cohesion, thus offering guidance for future research efforts (Lu et al., 2020).

Selection bias presents a persistent challenge in systematic reviews, particularly when utilizing search engines like Google Scholar, which prioritize results algorithmically. In this review, a deliberate strategy was implemented to mitigate this bias by incorporating random selection methodologies. Articles were chosen based on established inclusion criteria, focusing on empirical relevance and methodological rigor. However, the reliance on AI-generated recommendations introduces a potential preference for more recent or widely disseminated studies, potentially overlooking less visible yet high-quality research. A combination of automated and manual search techniques was therefore employed to ensure a balanced representation, enhancing the reliability and comprehensiveness of the review (Acheampong et al., 2021).

The review period, spanning 2013 to 2023, was selected to encompass significant advancements in AI-EI technologies. However, this delimitation could introduce detection bias by excluding earlier studies that may have laid the groundwork for current applications. To address this, frequently cited foundational studies were included, even if they fell outside the specified range. Furthermore, the review continuously reassessed the relevance of the time frame in light of evolving workplace dynamics and technological progress. This adaptive approach ensured a comprehensive analysis, integrating both historical and contemporary perspectives to provide a holistic understanding of the field (Mantello et al., 2021).

Attrition bias occurs when eligible studies are excluded based on subjective preferences or perceived misalignment with the review's objectives. To counter this, an objective scoring system was employed, evaluating factors such as methodological robustness, consistency with the research question, and contextual relevance. Despite these measures, some studies may have been excluded due to minor deviations from the predefined criteria, potentially omitting valuable insights. The documentation of exclusion criteria and transparent evaluation practices mitigates this risk, ensuring the reproducibility of the review while acknowledging its limitations (Roemmich, 2023).

Synthesizing the collected data required robust analytical tools to distill meaningful patterns and insights. This review utilized clustering techniques such as Forest Plots, which visually represent aggregated results from multiple studies. These tools highlighted commonalities and variabilities across findings, such as consistent improvements in job satisfaction attributed to AI-EI systems. Meta-analyses enabled deeper exploration of these trends, offering quantitative validations of observed patterns. For instance, Forest Plots identified significant positive correlations between the use of AI-EI technologies and enhanced team cohesion, reinforcing the practical value of these systems (Liu et al., 2021).

The review adhered to strict inclusion criteria, focusing exclusively on empirical studies exploring the effects of AI-EI technologies in workplace settings. Studies were required to report measurable impacts on well-being or productivity and to be peer-reviewed. The exclusion criteria eliminated theoretical research, studies conducted outside organizational contexts, and non-peer-reviewed publications. While this approach ensured methodological rigor and relevance, it also limited the scope by excluding potentially insightful theoretical analyses. Future reviews should aim to integrate empirical and theoretical perspectives to enrich the understanding of AI-EI systems' multifaceted impacts (Yang et al., 2022).

3 Emotional Artificial Intelligence in the workplace

Emotional artificial intelligence is transforming work environments, redefining interactions, productivity and organisational dynamics. Figure 1 proposes a taxonomy based on four key dimensions, organised in a hierarchical pyramid, which provides a holistic view of its applications and challenges. At the base is the organisational dimension, which analyses the impact of emotional AI on productivity, team cohesion and organisational culture. This is followed by the application dimension, which explores the use of emotional AI tools in activities such as emotion analysis and process personalisation. The ethical and regulatory dimension addresses critical issues such as privacy, algorithmic bias and the need for clear regulations for responsible implementation. At the top of the pyramid is the technological dimension, which includes the models and algorithms that drive these innovations, such as neural networks and generative models. This taxonomy provides a framework for analysing and harnessing the potential of emotional AI, balancing technological innovation with ethical and organisational responsibility:

- Technological Dimension: Focuses on the development, implementation, and optimisation of AI algorithms and tools for detecting and analysing emotional cues in workplace settings. Includes advancements in machine learning, data processing, and integration of IoT devices to enhance emotional AI systems.
- Ethical and Regulatory Dimension: Addresses the ethical concerns and regulatory frameworks necessary for the responsible use of emotional AI in workplaces. This includes privacy, data security, employee consent, and fairness to ensure ethical deployment.
- Application Dimension: Explores the practical use cases and applications of emotional AI in the workplace, such as improving employee well-being, enhancing team dynamics, and personalising training programmes to boost productivity and satisfaction.
- Organisational Dimension: Examines the broader impact of emotional AI on workplace culture, leadership styles, and organisational strategies. It includes fostering a supportive work environment and aligning AI use with organisational goals and employee engagement initiatives.

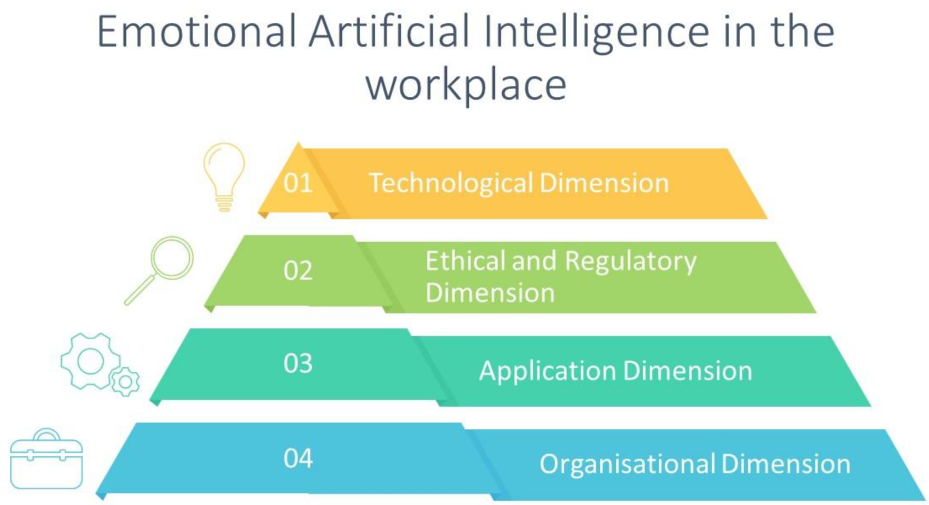

Fig. 1 Emotional Artificial Intelligence for the workplace.

3.1. Technological Dimension of Emotional Artificial Intelligence in the workplace

In this paper, we will focus on the Technological Dimension of Emotional Artificial Intelligence in the workplace. This dimension encompasses the development and optimisation of advanced algorithms, machine learning models, and data processing techniques aimed at detecting, analysing, and interpreting emotional cues. Our emphasis will be on exploring the technological innovations and tools that enable the effective implementation of emotional AI systems, ensuring their accuracy, reliability, and scalability in workplace environments. By delving into this dimension, we aim to provide a comprehensive understanding of the current advancements and challenges in the technological framework of emotional AI. The technological dimension of Emotional AI Algorithms and Models at work encompasses advances such as:

- Convolutional Neural Networks (CNN). Convolutional neural networks (CNNs or ConvNets) are a popular group of neural networks that belong to a wider family of methods known as deep learning. The secret for their success lies in their carefully designed architecture capable of considering the local and global characteristics of the input data (Pinaya, Vieira, Garcia-Dias & Mechelli, 2020).
- Recurrent Neural Networks (RNN). Recurrent Neural Networks (RNNs) are a type of neural network architecture which is mainly used to detect patterns in a sequence of data. Such data can be handwriting, genomes, text or numerical time series which are often produced in industry settings (stock markets or sensors) (Schmidt, 2019).
- Transformer and BiLSTM models. The proposed model is a Transformer-BiLSTM fusion neural network designed for network intrusion detection, utilizing data enhancement and feature enhancement techniques to improve detection accuracy and generalization ability (Xiang & Li, 2023).
- Generative Models. Generative models are a class of machine learning models designed to generate new data similar to the training data. Examples include Generative Adversarial Networks (GANs) and Generative Pre-trained Transformers (GPT). GANs consist of two neural networks, a generator and a discriminator, that work together to produce realistic synthetic data. GPT models use transformer architectures to generate coherent and contextually relevant text (Bengesi, et al., 2023).
- Extended Reality. Extending Reality (XR) encompasses Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR). XR describes all real-and-virtual combined environments between human and computer input. VR, AR, and MR are all covered in this review, but we will refer to them as XR for clarity. VR refers to a computer-generated, fully artificial digital environment in which a user can perceive and interact with the environment through a variety of peripheral devices (Alnagrat, et al., 2022).
- Virtual Reality for emotion simulations. Compared with the classes conducted with methods that do not employ VR, the level of positive emotions increases in classes on the same subject conducted with this tool. An increase in positive emotions was observed both in those with low or high self-esteem. In the case of

negative emotions, it was observed that in those with low self-esteem, the intensity of negative emotions decreases, reaching the level presented by those with high self-esteem (Ślósarz, et al., 2022).

- Augmented Reality for real-time emotional sensing. Augmented Reality (AR) for real-time emotional sensing involves using AR technology to detect and visualize users' emotional states in real-time. This technology enhances human-computer interaction by providing immediate feedback on emotional responses, which can be used in various applications such as mental health monitoring, interactive gaming, and personalized marketing. This real-time emotional sensing capability allows for more intuitive and responsive interactions, ultimately improving user experience and engagement (Şemsioğlu, et al., 2022).
- Internet of Things (IoT). The IoT refers to networks of heterogeneous devices rather than traditional networks of homogeneous devices. Things, in the IoT, involve a variety of embedded devices and smart objects whose interconnection is expected to enable advanced & intelligent applications and to make the communications and automation, mostly in all areas, easier and achievable (Abdul-Qawy, et al., 2015).
- Emotional sensors in wearable devices (wearables). The emulation of emotional states allows machines to represent some human emotions. This artificial representation of emotions is being used by machines to improve the interaction process with humans. In order to create a fluid emotional communication between human and machines, the machines need first to detect the emotion of the human with the final purpose of improving human-computer interactions (Rincon, et al., 2017).
- Environmental monitoring to influence well-being. Environmental monitoring to influence well-being involves the systematic collection and analysis of environmental data to assess and improve the health and quality of life of individuals and communities. This approach aims to identify and mitigate environmental factors that negatively impact well-being, such as air and water quality, noise levels, and exposure to pollutants (McGrath & Ní Scanaill, 2014).
- Cloud computing. Now there are lots of definitions and metaphors of cloud computing. From our points of view, cloud computing is a kind of computing technique where IT services are provided by massive low-cost computing units connected by IP networks. Cloud computing is rooted in search engine platform design (Qian, Luo, Du & Guo, 2009).
- Emotional big data processing. Emotional big data processing involves the collection, analysis, and interpretation of large volumes of data related to human emotions. The goal is to gain insights into emotional trends and behaviors, which can be applied in fields like mental health, marketing, and human-computer interaction (Sahoo & Kavya, 2024).
- Scalable platforms for real-time emotion analysis. Scalable platforms for real-time emotion analysis refer to advanced technological frameworks capable of processing and interpreting large volumes of emotional data in real-time. The scalability of these platforms ensures they can handle vast amounts of data efficiently, making them suitable for applications in mental health monitoring, customer service, and interactive media (Fora Soft., 2024).
- 5G and Advanced Connectivity. The fifth generation (5G) of wireless communication technology offers higher data rates, lower latency, increased network capacity, and a better user experience compared to its predecessors (3 G and 4 G). Te 5G NR includes smart factories, smart cities, smart homes, factual reality, seamless connectivity in self-driving cars, and telemedicine (Tiwari, et al., 2023).
- Instant communication for remote emotional monitoring. Instant communication for remote emotional monitoring refers to the integration of real-time communication technologies, such as video calls, chat applications, and wearable devices, to continuously monitor and assess emotional states remotely. This approach enables timely interventions and support, enhancing mental health care and emotional well-being (Zhou & Li, 2023).

Tables 1 and 2 provide a comprehensive analysis of algorithms and models applied in workplace emotional AI. Table 1 focuses on detailing the methodologies, feature extraction techniques, datasets employed, and application domains, highlighting their effectiveness, accuracy, and limitations. Similarly, Together, these tables present a holistic view of the advancements and challenges in workplace emotional AI research.

Table 1. Comprehensive analysis of algorithms and models applied in workplace emotional AI.

Model/Algorithm	Workplace Application	Related Work
Convolutional Neural Networks (CNN)	Emotional patterns in emails and internal communications may be identified to support organisational well-being management.	Kim et al. (2022)
Recurrent Neural Networks (RNN)	Stress and negative emotions in meetings and collaborative environments can be detected to facilitate proactive interventions.	Hong et al. (2021)
Transformer and BiLSTM Models	Team dynamics may be enhanced by monitoring real-time group conversations, allowing leadership to adjust strategies accordingly.	Sharma et al. (2023)
Generative Models (e.g., GPT, GANs)	Empathetic chatbots can be developed to support mental health and well-being through personalised recommendations.	Liu et al. (2023)
CNN-RNN Hybrid Models	Visual and textual data from video calls and written messages can be integrated to enable more holistic emotional analysis.	Zhou et al. (2021)
GANs for Emotional Augmentation	Emotional datasets may be expanded to improve detection models in workplace environments through the generation of synthetic data.	Lu et al. (2020)
Hierarchical Attention Networks	Emotions in emails can be classified to prioritise responses based on the sender's emotional state, thereby optimising communication.	Chen et al. (2022)
Multimodal Fusion Models	Emotions in hybrid (remote/in-person) interactions may be analysed using multiple data sources to inform personalised interventions.	Singh et al. (2023)
Deep Reinforcement Learning (DRL)	Recommendations can be adapted in real time based on detected emotional states, which may assist in managing stress and improving productivity.	Ma et al. (2023)
Self-Supervised Learning (SSL)	Emotion detection models may be trained without labelled data to identify emotional shifts in hybrid work settings.	Zhou et al. (2023)
Graph Neural Networks (GNNs)	Team emotional dynamics can be analysed by modelling complex relationships, which may contribute to enhancing team cohesion through adaptive strategies.	Al-Saadawi et al. (2024)
Neural Style Transfer (NST)	Negative expressions in emails may be automatically transformed into more constructive forms, potentially improving communication effectiveness.	Hazmoune, S. et al. (2024)
Contrastive Learning (CL)	Sentiment analysis in feedback can be refined to help identify employee concerns and strengthen engagement.	Lee et al. (2023)

Table 2. Comprehensive analysis of algorithms and models applied in workplace emotional AI.

Model/Algorithm	Workplace Application	Related Work
Recurrent Neural Networks (RNN)	Monitoring systems may be applied to evaluate employees' emotional well-being by analysing speech and text patterns over time, allowing the detection of stress or fatigue.	Patwardhan & Knapp (2016).
Transformer and BiLSTM Models	Real-time emotional detection in group conversations can be used to support team cohesion and performance.	Urquhart, Laffer & Miranda (2022).
Generative Models (GPT, GANs)	AI-driven conversational agents may be developed to interpret emotional cues and provide empathetic responses that can contribute to improving communication and support.	Mantello, Ho, Nguyen & Vuong (2021).
Hierarchical Attention Networks (HAN)	Emotion classification in emails can be implemented using context-aware encoding, enabling response prioritisation and potentially reducing emotional overload for employees.	Chen et al. (2022).
Multimodal Fusion Models	Multimodal approaches combining text, audio, and facial expression data may be used to perform real-time emotional analysis in hybrid work environments, thereby supporting team dynamics.	Singh et al. (2023)
GANs for Emotional Augmentation	Synthetic emotional datasets can be generated to support the training of AI systems, contributing to more robust and realistic emotion detection in workplace settings.	Lu et al. (2020)
Hybrid Neural Networks (CNN-RNN)	The integration of video imagery and textual data may enable the assessment of emotions in virtual meetings, supporting real-time identification of group dynamics and emotional states.	Zhou et al. (2021)
Extended Reality (XR)	Augmented and virtual reality tools can be utilised to simulate emotional work environments for stress management training and real-time well-being monitoring.	Yang, Rahmanti, Huang & Li (2022).
IoT and Emotional Sensors	Wearable sensors may be incorporated to capture physiological data, such as heart rate and cortisol levels, which can assist in preventing burnout and monitoring stress.	Mantello, Ho, Nguyen & Vuong (2021).
Emotional Big Data	Large-scale emotional data can be	Poria, Majumder, Hazarika &

Platforms	processed using cloud computing to provide predictive analytics for organisational well-being and team dynamics.	Mihalcea (2019).
5G Connectivity Optimization	Remote emotional monitoring systems may facilitate real-time interventions, enabling responsive emotional support in decentralised teams.	Amar, Parikh, Arora, McConnell, & Cornwall (2024).

3.2. Ethical and Regulatory Dimension of Emotional Artificial Intelligence in the workplace

The increasing adoption of explainable artificial intelligence (XAI) systems raises significant challenges related to privacy and consent, particularly in applications involving the collection and analysis of emotional data. According to Zhang et al. (2024), explanations generated by XAI models may inadvertently reveal sensitive information about the data used for training, exposing individuals to potentially significant privacy risks. These risks include membership inference attacks, data reconstruction, and model extraction attacks, which can compromise both the identity and emotional data of users. The article highlights the need to develop robust countermeasures, such as data masking techniques and differentially private learning algorithms, to safeguard privacy in XAI systems. Moreover, the authors emphasize that achieving a balance between transparency and privacy is likely to be crucial for fostering user trust in these systems. In this context, implementing mechanisms that ensure informed and explicit user consent appears to be an essential component of the ethical design of XAI technologies that handle emotional data.

The use of artificial intelligence systems in career development raises significant ethical challenges related to privacy and consent in the collection and use of emotional and behavioural data. According to Shepherd et al. (2024), employees' perceptions of fairness, transparency, and privacy intrusion tend to depend on the source of the data used (internal or external) and the degree of human involvement in automated decisions. Systems that integrate external data, particularly without the explicit knowledge or consent of employees, may generate distrust and perceptions of privacy invasion. Furthermore, a lack of transparency in how these systems make automated decisions can reduce employees' satisfaction with the process and may increase concerns about the control of their personal data. These findings highlight the importance of designing AI systems that prioritise transparency, ethics, and informed consent to ensure employee trust and acceptance. This approach may help to mitigate privacy concerns while fostering perceived fairness and satisfaction in the use of AI technologies in the workplace.

The use of artificial intelligence systems for automated crowd analysis poses significant ethical and legal challenges, particularly concerning privacy and consent in the collection of emotional data. According to Fischer and Bonatti (2024), these systems, which include emotion recognition technologies, may compromise individual autonomy by collecting and analysing sensitive data without explicit consent. The authors emphasise that current regulations, such as the General Data Protection Regulation (GDPR) and the European Union's AI Act, provide basic protections but may fall short in fully addressing the nuances of emotional privacy in public settings. Additionally, the article highlights how emotional data collection practices can exacerbate social inequalities by discriminating against certain demographic groups, especially when algorithms lack transparency and fairness. To mitigate these risks, the authors recommend implementing less invasive data analysis technologies and strengthening policies around informed consent. This approach may contribute to protecting individual privacy while fostering public trust in the ethical use of AI technologies in sensitive environments.

The integration of digital twins (DTs) in various industries has raised significant concerns regarding privacy, particularly when these technologies aggregate sensitive personal data, including emotional data, from multiple sources. According to Mehra and Agarwal (2024), digital twins may pose unique privacy risks, as they enable the assembly of disparate pieces of personal information into a comprehensive digital representation of individuals. This aggregation process can occur without explicit user consent, raising ethical questions about autonomy and transparency. The article emphasises that the inherent capability of DTs to analyse behavioural and emotional patterns may amplify these risks, particularly in contexts where such data is used for predictive analytics or decision-making processes. To address these challenges, the authors advocate the use of advanced privacy-preserving techniques such as pseudonymisation and synthetic data generation. These approaches aim to mitigate the risks associated with data aggregation while preserving the functionality of DTs for large-scale data analysis. By implementing robust privacy safeguards and ensuring informed user consent, organisations may be able to build trust and ethically leverage DT technology without compromising individual privacy.

The integration of artificial intelligence in critical care nursing introduces significant challenges and opportunities, particularly regarding perceptions of fairness and trust in AI systems. According to Hassan and El-Ashry (2024), building trust in AI tools is likely to depend on transparency and clear communication of how these systems generate recommendations. Critical care nurses emphasised that the black-box nature of some AI algorithms may undermine trust and limit their ability to confidently integrate AI outputs into patient care decisions. Furthermore, biases in AI algorithms, often stemming from non-representative training data, can lead to inequitable treatment decisions, further eroding confidence in these systems. The study highlights that fostering collaboration between nurses and AI systems, supported by user-friendly interfaces and transparent processes, may help to mitigate these challenges. Nurses also expressed the need for clear accountability frameworks to address ethical concerns, particularly when AI is involved in high-stakes decisions. Addressing these issues is likely to be essential for creating AI systems that align with principles of fairness, trust, and ethical patient care, enabling healthcare professionals to leverage AI as a tool to enhance, rather than hinder, their clinical expertise and decision-making.

Artificial intelligence systems are increasingly perceived as multifaceted challenges shaped by user evaluations of equity, transparency, and accountability, as reported by Salen et al. (2024). One of the primary obstacles to establishing trust lies in the presence of algorithmic bias. To address these concerns, the authors propose integrating ethical guidelines and enhancing transparency during the early stages of system design and implementation. Such measures are expected to strengthen confidence in AI outcomes and support alignment with broader social values. Prioritising these aspects may also facilitate clearer communication and the establishment of accountability mechanisms, thereby reinforcing organisational trust in AI technologies across diverse contexts.

The implementation of emotional AI should consider the potential consequences of manipulated emotions and their effects on employees. Striking a balance between enhancing productivity and managing the demands of emotional labour appears to be essential to ensure a healthy workplace environment.

The perception and interpretation of emotions vary significantly across cultures, presenting challenges for the deployment of emotional AI in global contexts. This section highlights the need to consider the establishment of universal standards for emotional AI to ensure equitable and culturally sensitive applications.

The integration of Artificial Intelligence into workplace dynamics offers significant benefits, such as improved efficiency, data-driven decision-making, and enhanced emotional intelligence applications. However, the growing reliance on AI in these settings introduces several risks associated with technological dependence:

- Erosion of Human Interaction. Over-reliance on AI-driven tools may reduce meaningful interpersonal communication among employees. Automated systems handling conflict resolution, team dynamics, or emotional support could undermine the importance of human empathy and understanding in the workplace.
- Overreliance on AI for Decision-Making. Employees and leaders may become overly dependent on AI to make key decisions, potentially ignoring contextual or nuanced factors that AI systems cannot process effectively. This could lead to decisions that lack human judgement, creativity, or moral reasoning.
- De-skilling of Workforce. Continuous use of AI for repetitive tasks or emotional analysis could lead to a reduction in employees' critical thinking, problem-solving, and interpersonal skills, creating a less adaptable workforce in the long run.
- Loss of Autonomy. Employees might feel their autonomy is undermined as AI systems increasingly monitor emotions, behaviours, and productivity. This could lead to resistance, stress, or disengagement from work, reducing overall morale.
- Ethical Dilemmas and Bias. Dependence on AI systems that analyse emotional dynamics may inadvertently propagate biases or misinterpret human behaviours. Trust in such systems could lead to flawed decisions, especially if ethical considerations are not prioritised in AI development.
- Vulnerability to System Failures. Overdependence on AI systems increases vulnerability to technical issues or cybersecurity threats, which could disrupt workplace operations or expose sensitive emotional data to breaches.

Mitigating these risks requires a balanced approach to AI implementation, emphasising its role as a supportive tool rather than a replacement for human judgement and interaction. Promoting digital literacy, maintaining transparency, and encouraging ethical

AI practices can help minimise technological dependence while fostering a harmonious integration of AI into workplace dynamics.

Application Dimension of Emotional Artificial Intelligence in the workplace

This section explores the use of emotional AI in talent acquisition and employee management. Emotional assessments during interviews allow for a better understanding of candidates' emotional intelligence and compatibility with workplace culture. Additionally, monitoring employees' emotional states can enhance job satisfaction by identifying and addressing potential concerns proactively.

Emotional AI enables adjustments in leadership styles to foster emotionally intelligent leadership. By leveraging tools like facial and voice recognition, organisations can analyse group dynamics, identify communication gaps, and improve collaboration and team performance.

Emotional AI systems can detect signs of stress and burnout by analysing physiological signals such as heart rate variability and facial expressions. These insights allow organisations to provide timely emotional feedback, promoting better mental health and overall employee well-being.

Emotional AI plays a key role in enhancing customer interactions. AI-powered chatbots and virtual assistants can interpret users' emotions and adapt their responses accordingly, creating more personalised experiences. Additionally, emotional AI aids in designing marketing strategies that resonate with customers by leveraging emotional cues and behavioural insights.

3.3. Result dimension analysis of Emotional Artificial Intelligence in the workplace

The integration of AI technologies into workplace settings has demonstrated significant improvements in individual employee satisfaction and overall well-being. Personalized adaptations provided by emotional AI systems enable the identification of stress triggers and the implementation of targeted interventions. For example, real-time feedback mechanisms facilitated by IoT wearables monitor physiological markers such as heart rate and cortisol levels, allowing employees to receive actionable recommendations to manage stress. Studies also show that emotional AI can foster self-regulation and mindfulness by offering tools such as relaxation exercises through empathetic chatbots. This human-centered approach to AI integration not only mitigates workplace stress but also enhances employees' emotional resilience and self-awareness, paving the way for healthier and more productive work environments (Kumar Valaboju, 2024).

Emotional AI has transformed organizational dynamics by enhancing team cohesion and reducing employee turnover. AI-driven tools like sentiment analysis systems and real-time emotion recognition models provide managers with valuable insights into team emotional states, enabling them to adapt leadership styles and foster collaborative environments. For example, BiLSTM-Transformer models have been utilized to detect emotions during group discussions, allowing managers to address tensions proactively. Furthermore, emotional AI systems enable continuous monitoring of employee satisfaction, helping organizations identify and address potential dissatisfaction before it leads to attrition. By aligning emotional insights with leadership strategies, organizations can maintain a motivated and cohesive workforce, thereby driving overall productivity.

The integration of emotional AI technologies has catalyzed innovation in human-computer interaction (HCI) and real-time decision-making platforms. Advanced tools like VR and AR are being used to simulate workplace scenarios, enabling immersive training programs for emotional intelligence development. Additionally, cloud-based platforms process large-scale emotional data in real time, facilitating predictive analytics that support organizational decision-making. These innovations are further enhanced by 5G connectivity, which enables instant communication and seamless integration of emotional AI tools in hybrid work environments. For instance, predictive algorithms integrated with HCI systems can offer decision-makers actionable insights into workforce emotional trends, ensuring timely interventions and promoting a technologically adaptive work ecosystem (Poria, Majumder, Hazarika, & Mihalcea, 2019).

The widespread adoption of emotional AI raises critical ethical and regulatory challenges, particularly regarding the collection and use of emotional data. Effective implementation requires robust informed consent protocols and compliance with data privacy laws to ensure employee trust. Additionally, cultural and regional differences influence perceptions of emotional AI, necessitating the development of adaptable and inclusive ethical frameworks. Organizations must also address the psychosocial impacts of emotional AI, including concerns about emotional manipulation and work-life balance, to create equitable and sustainable AI systems (Chen et al., 2022).

AI-powered emotional intelligence systems have been effectively deployed in talent management to enhance recruitment, employee engagement, and satisfaction. For instance, emotional analysis during interviews enables recruiters to assess candidate suitability based on emotional cues, such as stress responses or enthusiasm. Additionally, continuous emotional monitoring through IoT wearables supports the identification of factors contributing to job satisfaction, empowering HR departments to design initiatives that enhance workplace morale. By integrating these systems, organizations can optimize talent acquisition and retention, fostering a workplace environment that prioritizes both emotional and professional growth (Amar et al., 2024).

Emotional AI technologies contribute significantly to team productivity and dynamics by enabling emotional adjustments in leadership and group collaboration. Real-time emotional insights derived from voice and facial recognition models provide leaders with data to tailor their interactions, promoting emotionally intelligent leadership. Moreover, these tools support group dynamics analysis by identifying emotional patterns during meetings and collaborative tasks, facilitating conflict resolution and improved teamwork. Such applications underscore the potential of emotional AI to create cohesive teams that thrive in high-pressure scenarios, driving organizational success.

Incorporating emotional AI into workplace health initiatives has proven instrumental in identifying and mitigating stress-related conditions such as burnout. Physiological monitoring tools embedded in wearables detect early signs of stress, while personalized feedback platforms provide employees with mental health resources and strategies for improvement. For example, sentiment analysis combined with stress detection algorithms has been used to deliver tailored wellness programs, contributing to a healthier workforce. This proactive approach not only reduces healthcare costs but also fosters a culture of care and support within organizations, enhancing overall employee satisfaction and productivity.

Emotional AI is also transforming customer service and user experience through the implementation of empathetic chatbots and virtual assistants. These tools leverage sentiment analysis and natural language processing to adapt their responses to customer emotions, creating personalized and satisfying interactions. For instance, chatbots equipped with GPT-based models provide real-time support, addressing customer concerns with empathy and efficiency. Additionally, emotional AI enables the customization of marketing strategies based on consumer emotional data, enhancing engagement and loyalty. These applications demonstrate how emotional AI not only improves customer satisfaction but also drives business growth through emotionally intelligent service delivery.

Table 3: Focuses on key AI-EI technologies that enhance emotional intelligence across different fields such as education and workplace environments. Table 4: Explores AI applications in human capital management, highlighting their role in recruitment, training, and resource planning. Table 5: Discusses AI technologies specifically designed to improve workplace emotional well-being, addressing stress management and emotional assistance. Table 6: Examines gamification in workplace emotional management, emphasizing its role in engagement and stress relief. Table 7: Highlights how large language models (LLMs) integrated with emotional intelligence enhance employee well-being, emphasizing tailored responses and emotional monitoring.

Table 3: Key AI-EI technologies and their applications.

Technology	Description	Application
Sentiment Analysis	Identifies emotions in text and expressions.	Emails, social media
AI-Driven Emotional Coaching	Provides personalized emotional feedback.	Personal development
Empathetic Virtual Assistants	Chatbots that offer emotional support through real-time interactions.	Customer service
Contextual Learning Systems	Provide recommendations during key events such as presentations or high-stress scenarios.	Work presentations

Table 4: AI-EI technologies in human capital management.

Technology	Description	Application
Intelligent Recruitment Platforms	Identify suitable candidates using algorithms.	Recruitment and hiring

Predictive Analytics Systems	Anticipate staffing needs based on historical data.	Resource planning
Personalized Learning Systems	Adapt training content to employee needs.	Training and development

Table 5: AI-EI technologies for workplace emotional well-being.

Technology	Description	Application
Emotion Analysis Systems	Analyze language and behavior to identify emotional states.	Well-being monitoring
Emotional Wellness Applications	Provide guided meditation and stress management tools.	Stress management
Empathetic Chatbots	Offer real-time emotional support and mental health resources.	Emotional assistance

Table 6: AI-EI Technologies in gamification for emotional management.

Technology	Description	Application	Tools and algorithms	Reference
Gamified Learning Platforms	Include rewards, simulations, and leaderboards to enhance engagement.	Employee training and stress relief	Rule-based and reinforcement learning algorithms	Adhikari, K. (2020).
Virtual Emotional Support Assistants	Provide real-time feedback and personalized emotional support.	Emotional resilience programs	NLP-based chatbots and emotional analysis APIs	Adhikari, K. (2020).
Predictive Emotional Analytics	Detect emotional patterns and suggest personalized well-being activities.	Stress monitoring and intervention	Machine learning models and regression algorithms	Adhikari, K. (2020).

Table 7: LLM-empowered EI technologies in employee well-being.

Technology	Description	Application	Tools and algorithms
Real-Time Sentiment Analysis	Analyzes employee language to detect emotional cues and adjust responses.	Emotional monitoring	NLP and sentiment analysis APIs
Personalized Feedback Systems	Provides empathetic and tailored responses to employee interactions.	Employee support and training	Transformer-based language models (LLMs)
Empathetic Virtual Assistants	Offer emotional guidance and stress relief strategies.	Stress management and well-being	GPT-based chatbots and reinforcement learning models

Table 8: Details digital communication tools and their functions, focusing on improving team collaboration and workflows. Table 9: Showcases AI-integrated digital tools enhancing employee engagement through feedback, gamification, and mobile accessibility. Table 10: Highlights tools supporting virtual team collaboration, emphasizing asynchronous and real-time communication capabilities. Table 11: Lists AI-EI technologies promoting creativity and innovation, including generative AI and flexible team structures. Table 12: Focuses on real-time feedback and learning systems using AI to optimize HR processes and employee performance.

Table 8: Digital communication tools and their functions

Tool	Funtion	Purpose	Example technologies
Instant Messaging	Enables quick, real-time text communication.	Team coordination and Q&A	Slack, Microsoft Teams
Video Conferencing	Provides virtual face-to-face communication.	Meetings and brainstorming	Zoom, Google Meet
Corporate Blogs	Centralized posts for sharing insights and updates.	Knowledge sharing	Intranet blogs, SharePoint
Collaborative Platforms	Real-time document editing and teamwork.	Project collaboration	Google Workspace, Notion
Digital Feedback Tools	Facilitates continuous performance reviews.	Employee performance tracking	15Five, OfficeVibe

Table 9: Digital tools and AI functions for employee engagement.

Tool	Function	Purpose	Example technologies
Real-Time Messaging Apps	Facilitate instant communication among teams.	Quick updates and discussions	Microsoft Teams, Slack
Sentiment Analysis Systems	Analyze employee feedback to identify emotions and satisfaction levels.	Emotional well-being tracking	IBM Watson, Qualtrics
Personalized Feedback Platforms	Provide customized feedback based on individual performance.	Performance improvement	15Five, OfficeVibe
Gamification Platforms	Introduce game-like features to motivate participation.	Group challenges and achievements	Kahoot!, Centrical
Mobile Learning Applications	Provide training and information accessible from mobile devices.	On-the-go learning	Coursera, EdApp

Table 10: Digital tools for virtual team communication and collaboration.

Tool	Function	Purpose	Example technologies
Real-Time Messaging Apps	Facilitate instant communication among team members.	Quick updates and discussions	Microsoft Teams, Slack
Video Conferencing Platforms	Support virtual meetings and brainstorming sessions.	Collaboration and presentations	Zoom, Google Meet
Collaborative Document Platforms	Enable real-time document sharing and editing.	Asynchronous teamwork	Confluence, Google Docs
Visual Collaboration Tools	Allow for visual project planning and mind mapping.	Brainstorming and process visualization	Miro, Trello
AI-Based Features	Automate meeting schedules and provide sentiment analysis.	Optimize workflows and communication	Otter.ai, AI add-ons for Slack

Table 11: AI-EI technologies for creativity and innovation

Technology	Description	Application
Generative AI and LLMs	Automates data analysis and supports flexible team dynamics.	Self-organized, cross-functional teams
AI Robot Bosses	Optimizes decision-making for structured tasks.	Routine task management and efficiency

Table 12: AI-EI in real-time performance feedback.

Technology	Description	Application
Generative AI for HRM	Provides real-time performance evaluation and personalized feedback.	Employee engagement and motivation
Intelligent Tutoring Systems (ITS)	Personalize learning experiences with adaptive feedback.	Real-time learning and performance improvement

4 Discussion

The systematic review identifies significant trends in the development and implementation of artificial intelligence-based emotional intelligence (AI-EI) systems. The findings indicate that these technologies are primarily applied in areas such as talent management, organisational productivity, emotional well-being assessment, and team dynamics enhancement. For instance, deep learning models such as Convolutional Neural Networks (CNNs) and Transformer architectures are increasingly used to analyse emotions in real time through textual, visual, and vocal signals. However, the studies reviewed reveal critical gaps, including the lack of theoretical frameworks that holistically integrate emotional intelligence concepts with technological advancements. Additionally, there is a notable absence of longitudinal studies examining the sustained effects of these technologies on employees and organisations.

The review suggests that the findings align with established emotional intelligence theories, such as the Mayer-Salovey model, which emphasises the identification, understanding, and regulation of emotions, and Goleman's framework, which focuses on emotional competencies applied to leadership. AI-EI technologies may complement these approaches by offering tools for more objective, real-time emotion measurement, facilitating their practical application in organisational settings.

The practical implications derived from this review underscore the necessity of ethically and strategically implementing AI-EI systems. To maximise benefits, organisations are encouraged to train employees in the use of these technologies, fostering a culture of trust and transparency in emotional data handling. Integration with emotionally intelligent leadership policies is also recommended, whereby leaders use these systems not only for monitoring but also for supporting employee well-being through personalised interventions.

This study faces certain limitations that should be acknowledged. First, the geographical and contextual restrictions of the studies included may limit the generalisability of the findings. Most reviewed research focuses on developed economies, leaving a gap in understanding how these technologies might affect regions with limited technological resources. Second, potential biases in literature selection, such as the exclusion of studies in languages other than English or non-indexed articles, represent another challenge.

The review also identifies emerging applications with the potential to transform work environments. These include emotion analysis systems to identify group mood states, personalised learning platforms incorporating real-time emotional coaching, and empathetic virtual assistants providing continuous support to employees. These tools may enhance individual experiences and could also contribute to improving organisational productivity by optimising team collaboration and communication. However, these technologies raise potential ethical challenges, particularly in terms of transparency and equitable access.

AI-EI systems present significant ethical challenges related to the collection, storage, and use of emotional data. The lack of global regulations governing these technologies may increase the risk of data misuse and employee privacy breaches. Furthermore, methodological challenges include validating algorithmic models in diverse cultural contexts and integrating interdisciplinary approaches combining organisational psychology with data science.

Given the nascent nature of AI-EI research, future studies should prioritise longitudinal analyses examining the long-term effects of these technologies. Additionally, exploring how these tools can be adapted to different cultural contexts and economic sectors may provide valuable insights. Research could also examine the impact of technological governance policies on the acceptance and effectiveness of AI-EI systems and develop more robust metrics to assess their impact on organisational well-being and productivity.

In summary, AI-EI systems represent a significant evolution at the intersection of technology and organisational behaviour. While they offer opportunities to enhance well-being and productivity, their implementation requires careful and ethically informed approaches. Organisations will need to address both technical and ethical challenges to maximise the positive impact of these technologies.

Based on the results of this review, here are some useful suggestions, broken down by the type of organization:

- Corporate Sector: Use emotional AI tools in human resources, focusing on ongoing feedback, tracking employee well-being, and keeping an eye on ethics. Big companies should use AI that explains how it works and follow global rules for protecting personal data.
- Small and Medium Enterprises (SMEs): Begin with simple AI tools that can spot stress and gather feedback. Since these businesses have fewer resources, being open and getting employee permission should be their main focus when using these tools.
- Public Sector: Governments and public organizations should use emotional AI to understand public feedback, check on employee health, and improve public interaction. These uses should fit with national plans for digital governance and stress fairness, equity, and responsibility.
- Remote and Hybrid Organizations: Choose AI systems that quietly help with keeping employees motivated, offering support, and balancing work and personal life in setups that aren't all in one place. Making AI-EI solutions fit each organization's needs helps them work better and lowers possible ethical issues while making the most impact.
- Making AI-EI solutions fit each organization's needs helps them work better and lowers possible ethical issues while making the most impact.

5 Conclusions and future research agenda

The systematic review of artificial intelligence-based emotional intelligence (AI-EI) systems and their impact on employee well-being and organisational productivity highlights several significant contributions. Firstly, positive effects on employee attitudes are reported, including increased job satisfaction, motivation, and adaptability. Employees interacting with systems capable of understanding and responding to their emotions often report greater engagement with their workplace, which may contribute to reducing turnover and improving talent retention.

AI-EI systems may influence key organisational dynamics by shaping team cohesion, leadership styles, and trust. Leadership that integrates these technologies may be better positioned to respond to the emotional needs of their teams, thereby supporting more collaborative environments. This is likely to be particularly relevant in contexts characterised by continuous change driven by digital transformation. However, the need for more integrative research is emphasised to further examine the complex interactions between technology, human behaviour, and organisational dynamics.

Future research should consider focusing on several critical aspects to improve the implementation and impact of AI-EI systems. On one hand, contextual moderators, such as individual differences and organisational culture, need to be examined to better understand how these factors influence the effectiveness of these technologies. On the other hand, advanced methodologies such as immersive simulations and longitudinal analyses may provide deeper insights into the sustained effects of AI-EI on organisational well-being and productivity.

The integration of AI-EI is likely to reshape workplace and organisational dynamics. These technologies can enable the identification and response to emotional states through the analysis of facial, vocal, and physiological data, which may contribute to improving employees' emotional well-being and productivity. However, this advancement also introduces challenges related to balancing emotional automation with ethical sensitivity, ensuring these tools are not perceived as invasive. The key appears to lie in designing systems that prioritise human well-being while enhancing organisational efficiency.

A notable impact of AI-EI may lie in its potential to address mental health issues in the workplace. Emotional detection systems can help to identify early signs of stress, burnout, and demotivation, providing proactive tools for intervention. These systems may support mental health interventions while potentially contributing to reducing absenteeism and improving workforce retention.

The use of AI-EI raises significant ethical challenges related to privacy and informed consent. The collection and analysis of emotional data may be perceived as emotional surveillance, generating resistance among employees. To mitigate these risks, clear regulatory frameworks should be developed to support the protection of emotional data and promote responsible implementation.

The incorporation of AI-EI is also likely to transform the job skills required for the future of work. Employees may need to develop capabilities to interact effectively with emotionally intelligent technologies, alongside emotional intelligence competencies that complement automation. This includes managing their own emotions, fostering empathy, and building strong relationships in hybrid or virtual contexts. Therefore, continuous education and professional development are likely to become key pillars in preparing the workforce to meet the demands of an evolving work environment.

The potential of AI-EI can be understood in terms of its capacity to reinforce the human dimension of work through technological integration, rather than merely automating processes. Beyond automation, these tools may function as enablers that support employee well-being, creativity, and innovation. The success of AI-EI is likely to depend on human-centred design, prioritising not only efficiency but also authenticity in interactions and the promotion of an empathetic organisational culture. This approach may contribute to establishing a more balanced, sustainable, and well-being-oriented work model (Sarwar et al., 2024).

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