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Sopron, 2025. november 6.

6 November 2025, Sopron

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DEVELOPMENT TRAJECTORIES AND NEW DIVIDES IN TIMES OF SUSTAINABILITY TRANSITIONS

Szerkesztők / Editors:
RESPERGER Richárd, SZÉLES Zsuzsanna, TÓTH Balázs István

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TARTALOMJEGYZÉK / CONTENTS

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Emotional Artificial Intelligence in Interpersonal Leadership: Technological Implementation and Social Impact

Nils Andreas EIBER[1]
PhD Student
University of Sopron, Alexandre Lamfalussy Faculty of Economics, István Széchenyi Economics and Management Doctoral School, Sopron, Hungary

Prof. Dr. Rüdiger GRIMM[2]
Professor
FOM University of Applied Science for Economics and Management, Essen, Germany

Abstract:
Modern organisations face increasing social challenges in interpersonal leadership, as leaders must balance social responsibility, fairness and inclusion with the technological developments associated with digital transformation. Previous research on artificial intelligence (AI) in leadership has primarily focused on operational and strategic support, while the role of emotional artificial intelligence (EAI) in interpersonal leadership remains largely unexplored. This study examines how EAI can be integrated into leadership processes and how it influences relational dynamics and emotional well-being. The study applies a content analysis following Mayring and is structured according to a three-phase model of emotional information processing. The first phase is recognition, in which emotional cues are identified through text and speech analysis, facial expression analysis, physiological signals and multimodal emotion recognition. The second phase is processing, during which emotional patterns are classified using machine learning and deep learning methods and linked to leadership-relevant parameters. The third phase is reaction, in which EAI either supports the human leader by providing emotional insights through emotion analytics and feedback systems or operates autonomously by interacting with followers and guiding communicative processes through avatars or robotic systems. The findings highlight important implications for follower acceptance, regulatory requirements, particularly in relation to the EU AI Act, and the broader societal acceptance of EAI in leadership contexts.

Keywords: Emotional Artificial Intelligence, Affective Computing, Leadership, Human Resources
JEL Codes: M12, O33, Q01, J24, O33, M15

1. Introduction

Societal change and technological advancements are reshaping the demands placed on contemporary leadership. Public and scholarly debates increasingly emphasize fairness, inclusion, and sustainability, as well as emotional intelligence as a prerequisite for effective leadership. Concurrently, the integration of artificial intelligence (AI) into organisational structures is escalating, increasing its influence on leadership processes. This development has the potential to transform existing leadership practices and create new forms of leadership that are fundamentally shaped by the interplay between humans and AI systems.

Against this backdrop, the question arises how AI can support modern interpersonal leadership. Within the academic discourse, AI is situated along a broad spectrum of applications,

[1] nils.eiber@web.de (Corresponding Author)
[2] ruegrimm@t-online.de

ranging from supportive functions to autonomous, independently acting leadership forms (Derrick & Elson, 2019; Elsherif, 2024; Shahzad, 2024; Toniolo et al., 2020). Despite the growing scientific engagement with AI in leadership, current studies predominantly focus on operational and strategic domains. In contrast, the interpersonal dimension of leadership, and the extent to which AI can shape interpersonal processes, has received comparatively little attention.

In this context, the integration of emotional artificial intelligence (EAI) into leadership processes is becoming increasingly pertinent. EAI is defined by two core components: the recognition of emotional signals, adaptive emotion-aware responses, and the generation of emotional expressions (Nalepa et al., 2018; Schuller, 2018). The two approaches under discussion aim to make interpersonal dynamics in leadership situations more perceptible and intentionally shapeable. Preliminary studies suggest that the use of EAI can enhance the emotional intelligence of leadership, thereby facilitating more effective interpersonal leadership (Dwivedi, 2025, Elsherif, 2024;).

This raises the question which technical mechanisms underlie EAI and how they can be transferred into leadership processes. In light of this context, the present study addresses the following research questions:

RQ1: Which technical foundations and process steps characterize EAI?

RQ2: How can EAI be integrated into leadership processes?

2. Theoretical background

2.1. Leadership

Leadership is defined in diverse ways in the literature, with the approaches of Bass and Yukl considered particularly influential. Bass defines leadership as "Leadership is an interaction between two or more members of a group that often involves a structuring or restructuring of the situation and the perceptions and expectations of the members" (Bass, 2008). Yukl describes leadership as "Leadership is the process of influencing others to understand and agree about what needs to be done and how to do it, and the process of facilitating individual and collective efforts to accomplish shared objectives" (Yukl, 2013).

The concept of leadership can be further divided into two fundamental orientations: task-oriented leadership and relationship-oriented leadership. Task-oriented leadership includes behaviors that structure and coordinate work processes, clearly define goals and expectations, and systematically monitor performance to ensure efficient and effective task accomplishment (Yukl, 2013). Relationship-oriented leadership comprises behaviors characterized by empathy and emotional intelligence, the development of trust-based relationships, the support of individual needs, and open, appreciative communication. These behaviors aim to foster employee motivation, well-being, and collaboration (Yukl, 2013; Ojha et al., 2024).

2.2. Artificial Intelligence Leadership

AI leadership represents a subfield of leadership research and is defined differently across the literature. Kollmann et al. (2023) define AI leadership as follows: "artificial leadership, refers to a technology-based leadership style in which AI systems autonomously acquire data (digital source), analyze it through deep learning algorithms (digital analysis), and generate decisions that are accepted by followers as legitimate guidance (digital decision)". Harms and Han (2019), by contrast, describe AI leadership as "algorithmic leadership, refers to a form of leadership in which machines or programs take over tasks traditionally performed by human leaders, such as motivating, supporting, and developing followers".

In this context, the integration of AI is transforming the leadership process, as it not only supports but, in certain areas, also replaces human intelligence. This shift alters the distribution of responsibilities between human leaders and technological systems, leading to changes in the structure and dynamics of contemporary leadership practice.

In the extant literature, two conceptual forms of AI leadership are discussed: AI-Supported Leadership and Autonomous AI Leadership. The concept of AI-Supported Leadership encompasses a leadership style in which AI functions as a cognitive assistant to the human leader, performing supportive tasks. In this capacity, AI serves as an instrument for information processing and decision support, enhancing the leader's performance and the quality of their decision-making (Divya et al., 2024; 2024; Dwivedi, 2025; Elsherif, 2024; Vivek & Krupskyi, Zaidi et al., 2025). In contrast, Autonomous AI Leadership is a leadership form in which AI fully replaces the human leader and independently carries out leadership tasks (Al Farabe et al., 2024; Pei et al., 2024; Quaquebeke & Gerpott, 2023; Toniolo et al., 2020).

2.3. Theories of Emotion

In psychological research, various theories of emotion aim to explain the emergence and function of emotional processes. Ekman's theory of basic emotions posits the existence of emotions that are universally recognised, biologically grounded, and transculturally identifiable. These emotions are distinguished by distinct physiological, facial, and behavioural responses (*Figure 1*). The six basic emotions; joy, sadness, anger, fear, disgust, and surprise are understood as evolutionarily adaptive human reactions (Ekman, 1992; Ekman & Friesen, 1971).

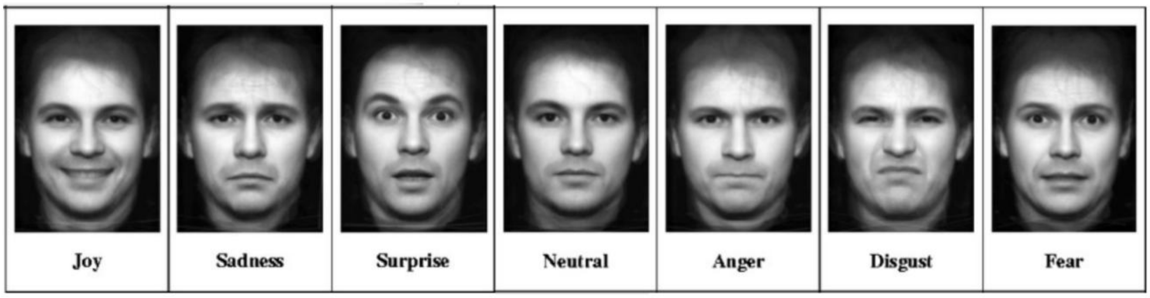

Figure 1: Illustration of the seven basic emotions

Source: Adapted from Atanassov et al. (2024), based on Ekman and Friesen (1978)

Because the concept of basic emotions captures the complexity of human affective states only to a limited extent, the dimensional approach has been proposed as a theoretical advancement. In the Circumplex Model of Affect, Russell (1980) conceptualises emotions as states located within a two-dimensional affective space (*Figure 2*). This conceptualisation is based on the idea that emotions are not discrete categories but continuously graded affective states, with valence (pleasure–displeasure) and arousal (activation–deactivation) serving as the fundamental dimensions. Consequently, the model provides a more nuanced and theoretically integrative representation of emotional experience than categorical approaches.

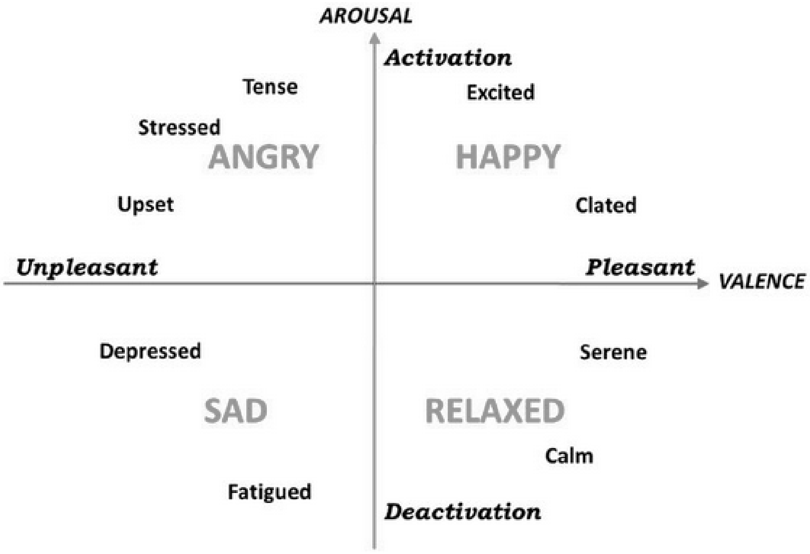

Figure 2: Illustration of the circumplex model of affect
Source: Adapted from Candra et al. (2015), based on Russell (1980)

As the third theoretical framework, Plutchik's Wheel of Emotions presents a model that encompasses eight primary emotions: joy, sadness, trust, disgust, fear, anger, surprise, and anticipation (*Figure 3*). The model arranges these emotions in four opposing pairs and maps their levels of intensity. Owing to its circular structure, it illustrates that emotions do not occur in isolation but exist in dynamic interrelationships, combining into affective states that vary in complexity and intensity (Plutchik & Conte, 1997; Plutchik, 2001).

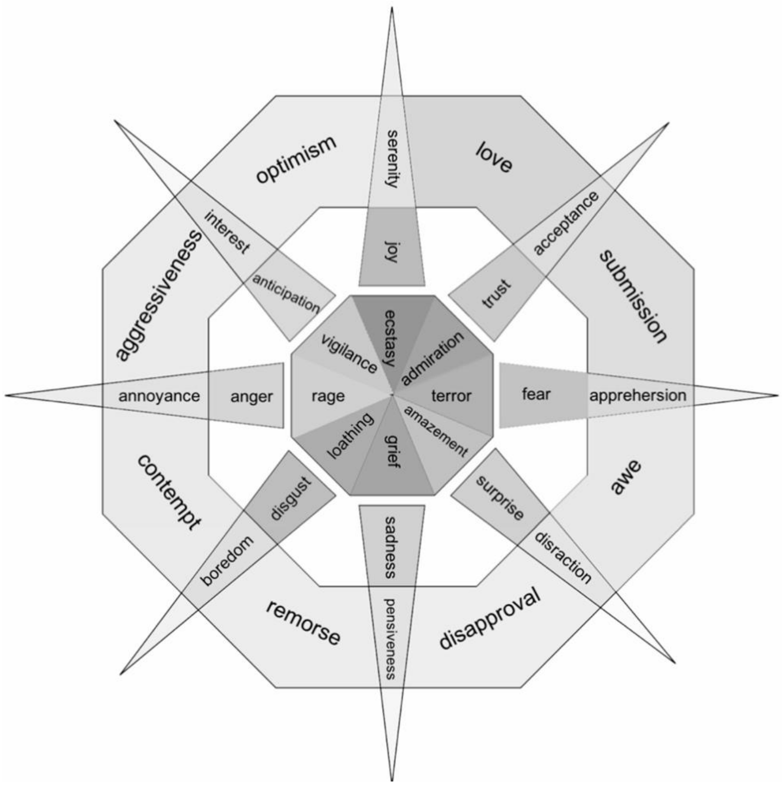

Figure 3: Illustration of Plutchik's wheel of emotions
Source: Adapted from Shu et al. (2018), based on Plutchik (2001)

2.4. Emotional Artificial Intelligence

The concept of EAI is grounded in the psychological definition of emotional intelligence as well as in the technological foundations of affective computing. Emotional intelligence is defined as the ability to accurately perceive and regulate one's own emotions, to self-motivate, to recognise emotions in others, and to manage interpersonal relationships effectively (Goleman, 1996). Furthermore, emotional intelligence is regarded as a central determinant of professional success, effective leadership, and social effectiveness (Goleman, 1999).

Affective computing is defined as "computing that relates to, arises from, or deliberately influences emotion" and refers to systems that not only capture emotional signals but also develop processes to interact with human emotions (Picard, 1997). Building on this, affective computing comprises methods that enable computers to recognise and express emotional patterns. Emotion recognition refers to the identification of recurring patterns, while emotion expression denotes their generation (Picard, 1997).

To facilitate these processes, affective computing systems draw on information from text, speech, facial expressions, and physiological signals. These constitute the fundamental modalities of emotion recognition and are used to detect and classify human emotions based on established emotion theories (Ho et al., 2021; Kanjo et al., 2015; Peters, 2021; Yusupova et al., 2021).

EAI refers to AI systems that capture emotional signals, interpret them within their situational context, and derive adaptive responses accordingly. It integrates the signal-oriented emotion processing of affective computing with the interpretive and response-based principles of emotional intelligence. From a functional perspective, EAI comprises three core phases:

- *Input:* Emotional information is captured.
- *Processing:* Detected emotions are analysed and interpreted in context.
- *Output:* The system generates adaptive responses to identified emotional states.

This characterises EAI as an approach that integrates emotional information into human–machine interaction (Picard, 2000; Schuller & Schuller, 2018; McStay, 2018; Nalepa et al., 2018; Svikhnushina & Pu, 2020).

3. Methodology

This study employs a scholarly literature review to systematically identify, conceptually situate, and further develop the current state of research on EAI in leadership contexts. Literature reviews enable a structured search, assessment, and synthesis of existing academic work and are regarded as an established methodological approach for analyzing prior research (Fink, 2005).

Given the dynamic, interdisciplinary, and methodologically diverse nature of the research field, a semi-systematic review design was selected. This approach is particularly suitable for topics that integrate technological and organizational perspectives and allows for a structured yet flexible identification and evaluation of relevant studies (Snyder, 2019).

For the methodological implementation, the SALSA framework by Booth, Papaioannou, and Sutton was applied, ensuring a transparent and reproducible procedure across the stages of Search, Appraisal, Synthesis, and Analysis (Booth et al., 2012).

The literature search was conducted between 1 October and 5 November 2025 in the databases Scopus (Elsevier) and Google Scholar to ensure the most comprehensive identification of relevant academic contributions. The search was performed across the fields of title, abstract, and keywords. Keyword combinations were drawn from the domains "Emotional Artificial Intelligence," "Affective Computing," "Artificial Intelligence," and "Leadership." No restrictions were applied regarding language, publication type, or journal ranking.

The selection of literature was based on clearly defined inclusion criteria to ensure thematic relevance and coherence with the research question. Included were scholarly works that (1) provide a theoretical or empirical contribution to the field of AI Leadership, (2) address EAI in a leadership context, (3) discuss technical aspects of implementing EAI or Affective Computing, or (4) demonstrate conceptual links to the process phases of input, processing, and output in emotional AI. In addition, the publications had to be available in full text and meet recognised academic standards. The screening process comprised title, abstract, and full-text review. In total, 75 scientific publications were included in the final review.

The analysis was conducted using qualitative content analysis according to Mayring. The procedure was based on a deductive category application in which relevant categories were defined in advance on the basis of theoretical considerations (Mayring, 2015). This deductive approach allows for theory-driven structuring of the material and ensures alignment with established conceptual models and recognised research logics. The categories were guided by the three central process phases of EAI:

- Input,
- Processing,
- Output.

This structure served as an analytical framework to systematically capture, categorise, and analyse the technological approaches, methodological procedures, and theoretical contributions of the identified literature.

4. Results

4.1. Technical Foundations of Emotional Artificial Intelligence (RQ1)

In the following section, the findings are presented along the three process stages of EAI: input, processing, and output. Subsequently, the various emotion-recognition modalities are described based on their respective characteristics.

The input phase begins with signal acquisition, which involves capturing emotional information that represents different manifestations of affective states and is recorded through various emotion-recognition modalities using technical devices (Schuller, 2018; Schuller & Schuller, 2018; Shu et al., 2018).

In the processing phase, the collected raw data are cleansed, normalised, and transformed into a consistent analytical format as part of data preprocessing, ensuring reliable downstream processing (Kanjo et al., 2015; Kumar & Martin, 2022; Schuller, 2018). Building on this, feature extraction represents a central processing step in which emotion-relevant feature representations are derived from the preprocessed data (Kanjo et al., 2015; Kumar & Martin, 2022; Schuller, 2018; Mohammed & Hassan, 2021). Emotion recognition methods rely on annotated datasets that contain examples of emotional states and are used to train and evaluate model performance (Cherry et al., 2012; Jayasinghe et al., 2025; Mattern et al., 2023; Mollahosseini et al., 2017; Sham et al., 2023).

Model-based processing relies on two methodological approaches. Machine learning (ML) encompasses statistical learning techniques that use extracted features to model systematic relationships between feature representations and specific emotions through algorithmic models (Jayasinghe et al., 2025; Mattern et al., 2023; Shu et al., 2018; Yang et al., 2022). In contrast, deep learning (DL) employs neural network architectures that autonomously derive relevant feature structures directly from the input data in an end-to-end process, thereby replacing manual feature extraction. Through this approach, deep learning models learn underlying patterns independently, which functionally distinguishes them from traditional ML methods (Jayasinghe et al., 2025; Joshi et al., 2022; Mattern et al., 2023; Mollahosseini et al., 2017; Schuller & Schuller, 2018; Shu et al., 2018; Yang et al., 2022).

The output phase comprises the output generation stage, in which the system classifies the detected emotional state and presents it either as a discrete emotion category or as a continuously scaled affective dimension (Jayasinghe et al., 2025; Kanjo et al., 2015; Shu et al., 2018).

Based on the processing sequence described above, distinct emotion-recognition modalities can be differentiated, each capturing specific psychological expressions of emotions and operationalising them through technically recorded data sources. These modalities form the foundation for text-, speech-, facial-, physiological-, and multimodality-based approaches to emotion recognition, which are outlined in the following sections.

Text-based Emotion Recognition (TER) refers to techniques that identify emotional states based on textual input through the analysis of linguistic, semantic, and contextual cues. These cues are mapped onto affective meaning patterns. While sentiment analysis primarily captures the attitudinal polarity of a text, namely its classification as positive, neutral, or negative, TER aims to identify specific emotional states and thereby provides a more fine-grained differentiation of affect (Zad et al., 2021; Kanjo et al., 2015; Schuller et al., 2009; Yusupova et al., 2021; Cambria et al., 2017). In ML-based TER approaches, textual data are transformed into structured representations such as bag-of-words or term-frequency models, which are used as numerical input for classification (Schuller et al., 2009). Support Vector Machines are frequently used because they identify patterns in these features and assign them to emotional categories (Aman & Szpakowicz, 2007; Cherry et al., 2012; Cortes & Vapnik, 1995). Lexical resources such as WordNet-Affect are also applied to annotate words in the text with affective meanings (Aman & Szpakowicz, 2007; Cherry et al., 2012; Strapparava & Valitutti, 2007). In DL-based TER methods, contextual transformer models such as BERT are used. They represent text by processing bidirectional context and enable a more precise interpretation of emotional meaning (Devlin et al., 2019; Zad et al., 2021).

Speech Emotion Recognition (SER) refers to computational approaches that identify emotional states from acoustic speech signals. These approaches analyse prosodic features such as pitch, loudness, and speaking rate, as well as spectral characteristics of the vocal signal, including frequency distributions and timbre, to infer affective patterns (Behn et al., 2024; Eyben et al., 2015; Jayasinghe et al., 2025; Ho et al., 2021; Kanjo et al., 2015; Schuller, 2018). SER systems commonly rely on datasets such as RAVDESS, which provide emotionally categorised speech recordings. Feature sets such as GEMAPS define standardised acoustic parameters that are frequently used for feature extraction in ML-based SER models (Eyben et al., 2015; Livingstone & Russo, 2018; Schuller, 2018; Schuller et al., 2009; Waleed & Shaker, 2025).

Facial Emotion Recognition (FER) refers to computational approaches that identify emotional states from visual facial information by analysing expressive movements and patterns and mapping them onto affective categories (Barros et al., 2020; Joshi et al., 2022; Mollahosseini et al., 2017; Peters, 2021). This approach builds on the Facial Action Coding System (FACS), a scientific coding framework that does not measure emotions directly but instead describes observable changes in facial musculature. FACS categorises these movements into clearly defined Action Units. These units can be combined to form characteristic emotional expression patterns (Ekman & Friesen, 1978). FER methods rely on large-scale datasets that provide a broad range of reliably annotated facial expressions. AffectNet is among the largest collections of emotionally labelled facial images and serves as a key foundation for modelling static facial emotions (Mollahosseini et al., 2017). Aff-Wild2 expands this perspective by incorporating video-based recordings of real-world interactions. This enables the analysis of dynamic expressive variations and temporal emotion trajectories (Kollias & Zafeiriou, 2019). Both datasets are widely used in ML- and DL-based FER systems and serve as essential empirical resources for deriving facial expression patterns.

Physiological Emotion Recognition (PER) refers to methods that identify emotional states based on physiological signals by capturing and analysing measurable biological responses. Core measurement modalities include electroencephalography (EEG), which records electrical brain activity; electrocardiography (ECG), which measures cardiac activity and heart rate variability; electromyography (EMG), which captures muscular activity; galvanic skin response (GSR), which measures skin conductance; respiration (RSP), which records breathing activity;

and temperature (T), which detects peripheral thermal changes. These signals are regulated primarily by the central and autonomic nervous systems and occur largely involuntarily. As a result, they often reflect emotional reactions more directly and reliably than observable expressive behaviours such as facial expressions or speech (Houssein et al., 2024; Kanjo et al., 2015; Khalane et al., 2023; Picard, 2000; Shu et al., 2018; Yusupova et al., 2021). A widely used dataset for PER is DEAP (Database for Emotion Analysis using Physiological Signals). It contains EEG, GSR, ECG, and RSP data, as well as synchronised facial video recordings collected during emotional stimulus presentation. DEAP therefore provides a comprehensively annotated corpus for analysing affective responses (Koelstra et al., 2011).

Multimodal Emotion Recognition (MER) refers to approaches that infer emotional states by integrating multiple modalities rather than relying on a single source of information. Because emotions are complex and multifaceted, unimodal methods are often insufficient to capture affective states reliably. MER therefore typically combines linguistic signals (TER), acoustic features (SER), visual facial information (FER), and physiological responses (PER). This enables emotional interpretation based on a broader and more heterogeneous data foundation. By consolidating these complementary sources of information, MER increases the consistency and robustness of emotion recognition, particularly in realistic and variable interaction contexts (Cambria et al., 2017; Chursinova & Stebelska, 2021; D'Mello & Kory, 2015; Khalane et al., 2025; Schuller et al., 2009; Yusupova et al., 2021; Lian et al., 2023).

Figure 4 presents a simplified technical illustration of the EAI process by integrating the three process phases of input, processing and output and showing their implementation across the various emotion recognition modalities (TER, SER, FER, PER, MER).

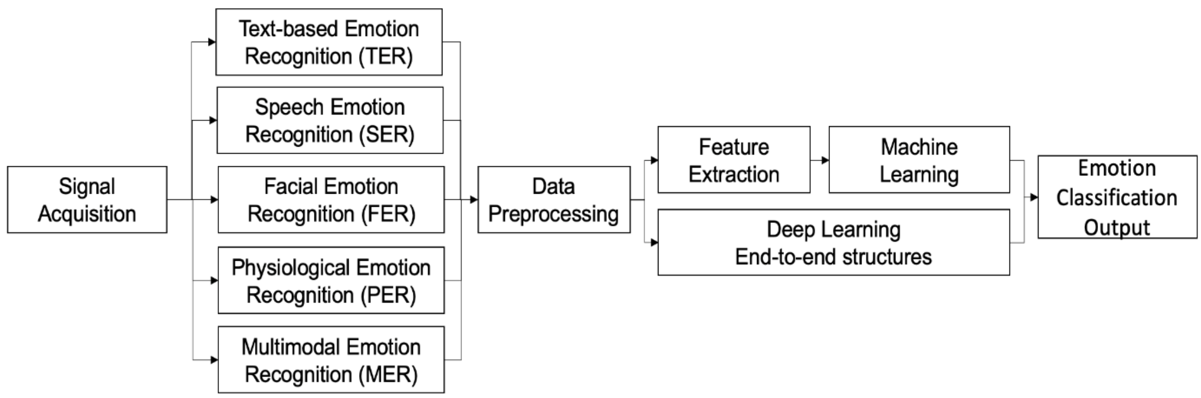

Figure 1: **Emotion recognition process**
Source: Own elaboration

4.2. Integrating Emotional Artificial Intelligence into Leadership Processes (RQ2)

In the following section, the results are presented to demonstrate how emotional signals can be captured as inputs within the leadership process and how EAI generates specific outputs that can be assigned to AI-Supported Leadership and Autonomous AI Leadership.

A wide range of interfaces capable of capturing emotional signals in leadership processes already exists, particularly through ubiquitous digital devices such as smartphones and computers (Kanjo et al., 2015; Yang et al., 2022; Bissinger et al., 2023; Joshi et al., 2022). Emotional signals can be identified through the analysis of text-based content, such as electronic mails or chat logs, which serve as input for TER on these devices (Bhusan & Jain, 2024). The integrated microphones of these devices enable the recording of vocal characteristics during phone calls or online meetings and provide the basis for SER (Behn et al., 2024; Yang et al., 2022). Furthermore, integrated cameras capture facial expressions during videoconferences, which can be analysed as part of FER (Bissinger et al., 2023; Ertay et al., 2021; Joshi et al., 2022; Kanjo et al., 2015).

In the context of videoconferencing, the integration of audio and video streams can generate multimodal inputs that are used for MER (Yang et al., 2022; Joshi et al., 2022). Methods also exist for capturing emotional signals directly in physical environments. In this context, real-time analysis is facilitated by fixed in-room cameras integrated into local, non-public CCTV systems. This approach contrasts with the utilisation of webcams in virtual meetings, where processing takes place remotely (Montri et al., 2025).

Within the domain of PER, the distinction of input signals is primarily determined by the modality of sensory acquisition. Sensor-based wearable systems encompass devices such as smartwatches, chest straps, and intelligent armbands that capture physiological parameters including ECG, GSR, RSP, or EMG (Kanjo et al., 2015; Schmidt et al., 2018; Gual-Montolio et al., 2022; Shu et al., 2018). Furthermore, non-wearable sensor systems function without direct bodily contact. In particular, thermal infrared imaging methods have been employed, in which thermal cameras detect minimal changes in skin temperature or peripheral blood flow to infer emotional activation (Spezialetti et al., 2020; Filippini et al., 2020).

Furthermore, there has been an increasing focus on forward-thinking approaches in which robot-assisted systems employ multimodal emotion recognition by integrating methods such as SER, FER, and PER, thereby integrating diverse emotional indicators within a unified analytical process (Mohammed & Hassan, 2021; Zhao et al., 2025).

The findings indicate that the output of EAI in the context of AI-Supported Leadership takes the form of emotion-aware responses. These are AI-driven feedback mechanisms or reactions triggered by the automated detection and evaluation of human emotional states. Overall, three types of output can be distinguished: emotion analytics systems, emotion-based cues, and emotion-aware feedback.

Emotion-analytics systems are designed to process detected emotional cues within a dashboard interface. The signals are presented in two forms: first, as aggregated retrospective status reports following virtual interactions; and second, as continuous real-time visualisations. The retrospective reports are based on the analysis of verbal and non-verbal cues, including participation patterns, emotional trajectories, and observable behavioural signals. By consolidating these emotional indicators, the system provides insights into group affect as well as the emotional responses of individual participants (Hegde & Jayalath, 2025; El Bahri et al., 2025; McDuff et al., 2019; Hasnine et al., 2023; Behn et al., 2024; Samrose et al., 2021). In the domain of leadership research, AI-supported analyses, including dashboard-based evaluations, have been shown to clarify emotional dynamics within teams (Quaquebeke & Gerpott, 2023; Dwivedi, 2025).

Emotion-based cue systems function as assistive technologies that capture emotional indicators in real time during virtual interactions. The behavioural and attentional markers identified by these systems include presence, attention levels over time, and their distribution within the overall group. Access to these real-time data is restricted solely to organisers (Kodithuwakku et al., 2022; Chow et al., 2025). Within leadership research, human leaders are reported to receive real-time insights into followers' emotional cues, such as information on current attentional states, observable emotional expressions, or emerging mood tendencies (Quaquebeke & Gerpott, 2023).

Emotion-aware feedback is defined as a form of output in which detected emotional cues are used to provide individuals with personalised responses regarding their own emotional state. One approach involves the system generating context-sensitive recommendations at the conclusion of an interaction by analysing previously recorded emotional trajectories and deriving suggestions for future adjustments (Samrose et al., 2021). Other systems deliver such feedback in real time during an ongoing interaction by translating identified emotional states directly into situational, regulatory, or adaptation-oriented recommendations (Liu et al., 2022; Harley et al., 2016). In leadership research, such systems are also described as providing feedback on the emotional states of human leaders or on aspects of their emotional intelligence. They can also formulate improvement-oriented recommendations based on these insights (Bhusan & Jain, 2024; Dwivedi, 2025).

The findings indicate that the output of EAI in the context of Autonomous AI Leadership extends beyond established emotion-aware responses and includes emotion expression. This refers to artificially produced, algorithmically generated, and contextually regulated emotional displays that are actively introduced into the interaction by the system.The outputs can be categorised into three distinct forms: conversational AI, avatars, and humanoid robotics.

Conversational AI refers to a form of AI in which verbal communication and emotional expression are generated through dialogue-based systems. This includes emotional dialogue systems that use natural language generation to produce semantically and emotionally appropriate responses. Such systems can simulate empathetic reactions and convey emotions through spoken or written language (Goel et al., 2021; Hegde & Jayalath, 2025; Zhou et al., 2018; Jolibois et al., 2025). Their output consists of autonomously regulated linguistic variations introduced by the system according to the situational context. These systems include chatbots and large language models such as ChatGPT (Schaaff et al., 2023; Zhang et al., 2024; Svikhnushina & Pu, 2020). Current leadership research has begun to examine such dialogue systems, particularly in scenarios where followers interact directly with the system to receive leadership-related feedback in real time (Madanchian et al., 2024).

Avatars represent an output modality that enables both verbal and non-verbal communication through a synthetically generated, digitally embodied appearance, which aligns with the concept of digital embodiment (Jolibois et al., 2025; ter Stal et al., 2020; Sham et al., 2023; Crowder & Carbone, 2023). Verbal communication is generated through natural language processing. Non-verbal communication is conveyed via a virtual face with movements, expressions, and facial cues that are precisely synchronised with the generated speech. This synchronisation enables consistent emotional interaction. This combination has been shown to enhance social presence and to make the interaction more authentic for interlocutors (Zhang et al., 2024; Fei et al., 2024; Sham et al., 2023). In this context, leadership research increasingly examines the extent to which embodied AI avatars can assume functions of human leaders and may be considered potential forms of leadership substitution (Derrick & Elson, 2018; Turcan et al., 2023).

Humanoid robots represent an advanced form of output in which verbal and non-verbal communication is realised through physically embodied, humanlike systems, which aligns with the concept of physical embodiment. Verbal communication is generated through natural language generation, whereas non-verbal communication is conveyed through bodily expressions such as gestures, facial expressions, and body movements. These communication modes are synchronised with high precision to create a coherent flow of interaction (Jolibois et al., 2025; Spezialetti et al., 2020; Sham et al., 2023). Through the integration of EAI, humanoid robots can display holistic empathic responses, which makes interactions appear more intuitive, authentic, and natural to human counterparts (Asada, 2014; Tsumura & Yamada, 2023). As robotic technologies continue to advance, leadership research increasingly examines the extent to which humanoid robots may assume leadership-relevant tasks in the future and operate as autonomous actors within formal leadership roles (Hubner et al., 2019; Hasenbein, 2023).

Figure 5 presents an integrative model derived from the findings of this study and illustrates how EAI is incorporated into the leadership process. It depicts how emotional input is captured and how output is generated in AI-Supported Leadership and Autonomous AI Leadership.

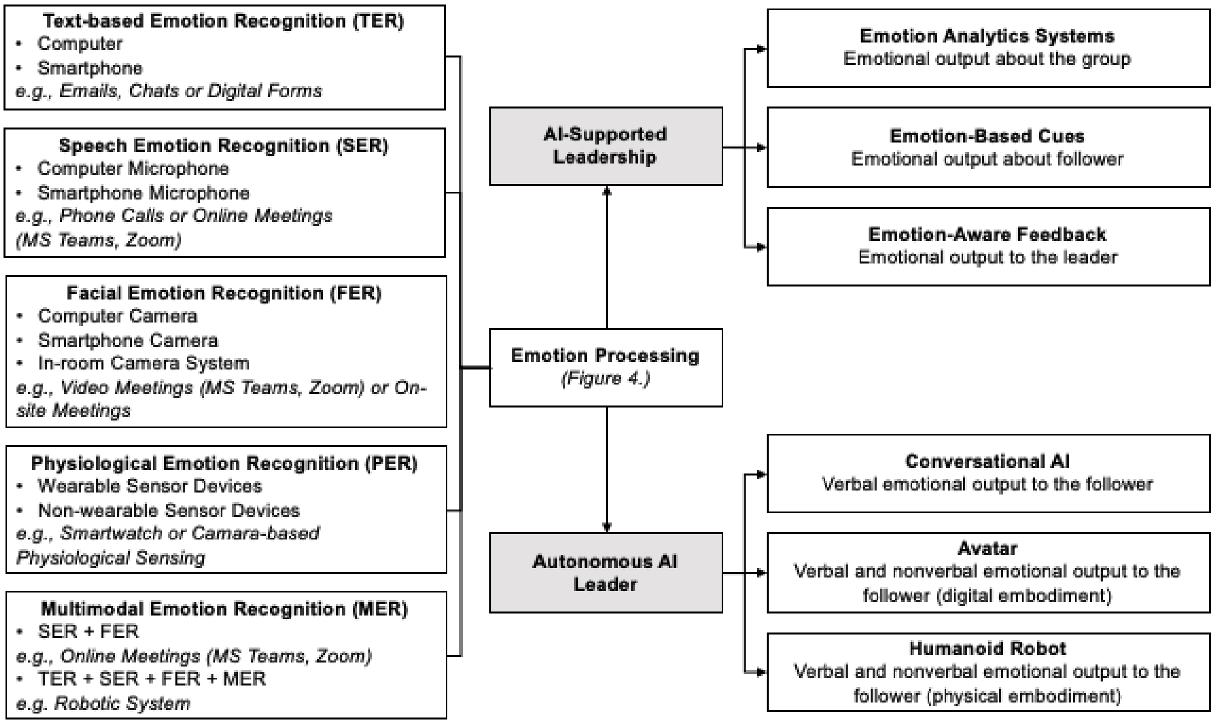

Figure 5. Emotional artificial intelligence integration model in AI leadership
Source: Own elaboration

5. Discussion

5.1. Interpretation of Findings

The findings indicate that EAI should be conceptualised as a procedurally structured system. The three-stage sequence of input, processing, and output demonstrates that emotional AI is grounded in the interplay between psychological expressions and technical data processing.

In the input phase, emotional signals can already be captured through widely used digital devices. Computers and smartphones continuously generate acoustic, visual, and textual data, suggesting that EAI should not be understood merely as a future concept but as an integral component of organisational infrastructures and digital leadership interactions. Affective data are therefore inherently available and technically accessible. Moreover, the extension of existing device infrastructures creates additional opportunities for data capture. The integration of supplementary sensing technologies, such as physiological wristbands or room-based CCTV systems, substantially expands the scope of emotional signal detection and may fundamentally reshape leadership interactions. Such expansion raises critical ethical concerns regarding transparency and the responsible use of additional emotional data. It necessitates a clearly defined organisational framework and strict compliance with applicable legal requirements.

With regard to recognition modalities, the analysis shows that TER, SER, FER, and PER capture only limited dimensions of emotional expression when applied unimodally. Reliable emotion recognition therefore depends on multimodal systems that integrate complementary signals and provide a more consistent, valid, and comprehensive data basis. The effectiveness of emotion-sensitive AI is consequently contingent upon the degree of multimodality, as this enables systematic compensation for the limitations of individual modalities.

In the processing phase, two principal technological approaches become apparent: classical machine learning methods and deep learning architectures. Whereas traditional machine learning relies on explicitly defined features, end-to-end deep learning models enable autonomous and more comprehensive feature extraction. This facilitates more precise identification of complex patterns and enhances the quality of emotion recognition. For leadership processes, these technological advancements increase the accuracy, contextual sensitivity, and robustness of emotional assessments.

The findings further demonstrate that EAI provides multiple forms of support within AI-Supported Leadership. The system identifies the emotional states of followers and the human leader and translates them into structured information. This includes indicators of group-level emotional dynamics, individual reactions, and feedback on the emotional conduct of the human leader in specific leadership situations. These functions can strengthen the human leader's emotional competence and enhance decision-making precision. Consequently, a fundamental aspect of conventional leadership is transformed. Emotions have traditionally functioned as a social source of information that the human leader was required to perceive and interpret independently. Through EAI, these informational processes become technically mediated and systematically structured, thereby shifting the epistemic basis of emotional evaluation. At the same time, responsibility and final decision authority remain with the human leader, who must critically evaluate, contextualise, and responsibly incorporate algorithmically generated emotional assessments into leadership decisions.

In the context of Autonomous AI Leadership, conversational AI, avatars, and humanoid robots are deployed. In this configuration, the role of EAI shifts from interpretative support to autonomous emotional interaction. As a result, the traditional exchange relationship between the human leader and the follower is reconfigured, with AI assuming direct relational interaction with the follower. As technological capabilities advance, the potential substitution of the human leader becomes an analytical consideration. However, such substitution would require AI systems to achieve communicative, social, and emotional effects that are functionally indistinguishable from those of a human leader. It remains uncertain to what extent followers would accept autonomous AI leadership, particularly in sensitive interpersonal contexts. Although AI systems may execute operational processes, responsibility and accountability cannot be transferred to technical systems. They must remain clearly assigned to human actors within the organisation through appropriate governance and oversight mechanisms. At present, the autonomy of such systems appears realistic only within clearly delineated domains of responsibility. Under current technological, social, and normative conditions, the complete substitution of the human leader by autonomous AI does not appear plausible.

Table 1 provides an integrative overview of the process phases, associated EAI capabilities, application areas, and their respective implications and risks.

Table 1: Integrative Overview of EAI Process Phases, Capabilities, Application Areas, and Implications

Process Phase	EAI Capabilities	Application Areas	Implications and Risks
Input (Data Capture)	• Emotion recognition via TER, SER, FER, PER and MER	• Use of existing digital communication interfaces (e-mail, chat, video meetings) • Expansion of sensing infrastructures (wearables, physiological and in-room monitoring systems)	• Privacy implications arising from the expansion of emotional data collection • Transparency challenges in the processing of affective data • Ethical tensions associated with emotion-sensitive AI systems • Legal and governance implications for organisational deployment
Processing	• Pattern classification via machine learning and deep learning	• Technological foundation for context-sensitive emotional assessment in leadership processes	• Multimodal emotion recognition (MER) enhances the validity and robustness of emotional assessment • Advanced deep learning architectures enable context-sensitive emotional assessment
Output (Response) AI-Supported Leadership	• Emotion Analytics Systems • Emotion-Based Cues • Emotion-Aware Feedback	• Group-level emotional output • Follower-level emotional output • Leader-directed emotional feedback	• EAI enhances the human leader's emotional competence and decision-making precision • EAI shifts the basis of interpersonal leadership by externalising emotion perception and evaluation • Decision authority remains with the human leader, requiring critical evaluation, contextualisation, and responsible incorporation of algorithmic assessments
Output (Response) Autonomous AI Leader	• Conversational AI • Avatar • Humanoid Robot	• Verbal emotional interaction with followers • Digitally embodied emotional interaction with followers • Physically embodied emotional interaction with followers	• Human leader replacement in interpersonal processes through direct AI–follower interaction • Dependence on advanced affective AI capable of replicating emotional intelligence • Acceptance and accountability challenges, as decision authority shifts to AI while responsibility must remain clearly assigned to human actors

Source: Own elaboration

5.2. Theoretical Implications

The findings indicate that the processing of emotional information within the leadership process is no longer exclusively conducted by humans. Instead, this process is increasingly supported technologically and evaluated on a data-driven basis. Consequently, EAI extends the conceptual foundations of emotionally intelligent leadership, as emotional perception and assessment are no longer solely contingent on the individual abilities of the human leader. The study introduces a technological dimension into existing leadership theories and redefines the nature of emotional interaction and influence within leadership processes. In AI-Supported Leadership, emotional perception remains embedded in the interaction between human leader and follower but is augmented by algorithmic assessments. Influence processes therefore become partially data-informed, while decision authority remains anchored in the human leader. In Autonomous AI Leadership, relational interaction is increasingly delegated to AI systems. Specific influence processes may be executed directly by AI. Nevertheless, normative authority and accountability remain anchored in the human actor despite operational automation.

5.3. Practical Implications

For practical application, it follows that organisations must develop clear governance and accountability structures to ensure that the use of EAI is transparent, ethical and operationally reliable. Leaders require competencies in the reflective handling of algorithmically generated emotion assessments to interpret and integrate them responsibly into decision-making processes. Autonomous forms of EAI can already relieve the human leader in clearly delineated areas by taking over specific and standardised leadership tasks, thereby reducing operational demands. EAI thus becomes an instrument that does not replace emotional leadership competence but rather extends it in a structured manner and supports the quality of leadership interactions.

5.4. Regulatory Implications (EU AI Act)

The findings demonstrate that EAI has the capacity to detect emotional signals and can be technologically incorporated into both AI-Supported and Autonomous AI Leadership. Concurrently, substantial legal constraints considerably restrict its implementation. A central constraint concerns the regulatory classification of EAI under the EU AI Act. The EU AI Act constitutes the European legal framework for the risk-based regulation of the development, provision and use of AI. It defines binding requirements for high-risk systems to safeguard security, transparency and fundamental rights. Furthermore, the Act classifies all forms of emotion recognition in the workplace as systems for monitoring, profiling or assessing individuals (European Parliament & Council of the European Union, 2024). EAI within leadership processes must therefore be classified as an “unacceptable risk” system under the EU AI Act, as it captures and analyses emotional signals in the workplace and uses them to inform leadership-related decisions (Figure 6). This highlights a structural tension between the technological potential of EAI and its regulatory admissibility in the European context. Whether future research will identify viable risk mitigation strategies or alternative application formats remains uncertain.

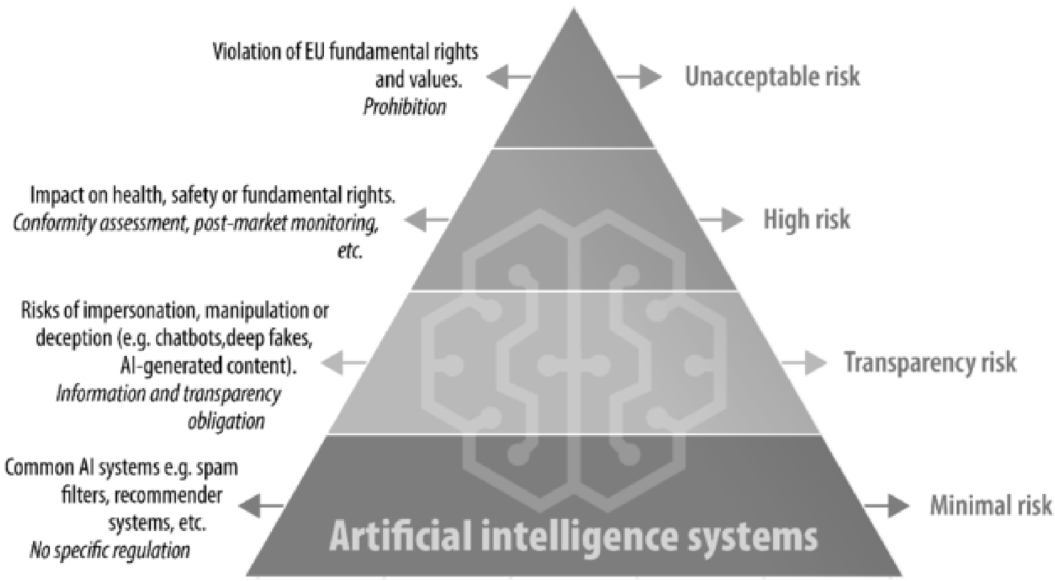

Figure 6: EU AI Act risk pyramid for AI systems
Source: Adapted from Chun et al. (2024)

5.5. Limitations and Future Research

The Empirical evidence on the acceptance of EAI in leadership processes remains limited. Future research should therefore examine how human leaders and followers perceive the use of emotion recognition in the input phase, as well as the various output forms of emotional AI across different AI leadership configurations. Qualitative approaches, such as expert interviews and focus groups, can provide initial insights into perceptions, legitimacy and trust formation. Building on these insights, quantitative studies should systematically examine key determinants of use and behavioural intention by drawing on established acceptance models such as TAM and UTAUT (Davis, 1989; Venkatesh et al., 2003; Zhang et al., 2025). Such multi-stage research designs provide a structured foundation for advancing empirical work on the acceptance of emotional AI in leadership contexts.

6. Conclusion

The present study set out to examine the potential of EAI to enhance interpersonal leadership. This was achieved by analysing both its technical foundations and its avenues for implementation within the leadership process. The study was based on a semi-structured literature review comprising 75 peer-reviewed publications, which were examined using qualitative content analysis following Mayring. The findings were structured along the process phases of input, processing and output.

The findings indicate that emotional signals can already be captured and technically processed through digital devices used in everyday life. Additional sensor technologies may further increase the precision of emotion recognition. Concurrently, unimodal approaches capture only partial aspects of emotional expression. Valid, context-sensitive and robust emotion identification is achieved only through multimodal methods combined with deep learning models.

In the context of AI-Supported Leadership, EAI generates responses that render both group-level emotional dynamics and individual emotional reactions of followers visible. It also provides indications regarding the human leader's own leadership behaviour. This approach expands emotional perception, a domain historically shaped primarily by human judgement. Consequently, it enables more precise assessments in leadership contexts. In Autonomous AI Leadership, EAI not only detects emotions but also autonomously generates corresponding emotional expressions. This development modifies the conventional relationship between human leader and follower. However, a complete replacement of human leadership does not appear feasible under current technological, social and ethical conditions.

From a managerial perspective, the implications differ according to the degree of autonomy. In AI-Supported Leadership, responsibility and final decision authority remain with the human leader. This requires competencies to critically interpret and responsibly integrate algorithmically generated emotional assessments into organisational decision-making. In Autonomous AI Leadership, operational processes may be executed by AI systems. Responsibility and accountability, however, cannot be transferred to technical systems. They must remain clearly assigned to human actors within the organisation through appropriate governance and oversight structures.

At the same time, the technological integration capability of EAI is in tension with the EU AI Act, which categorises emotion-recognition systems in the workplace as an "unacceptable risk" and imposes significant restrictions on their practical application. In addition, future research should examine the acceptance of emotional AI in leadership contexts and identify the conditions under which human leaders and followers support or reject the use of such technologies.

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