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ADVANCING HUMAN-COMPUTER INTERACTION: EXPLORING THE FRONTIERS OF ARTIFICIAL EMOTIONAL INTELLIGENCE IN INTERACTIVE SYSTEMS AND ITS IMPLICATIONS FOR SOCIETAL INTEGRATION

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Dr. Saman Javed
Department of Business Studies, Bahria University, Islamabad, Pakistan
Email: samanjaved95@gmail.com

ABSTRACT

Purpose: Advancements in both computer hardware and software fields are utilized to attain progress across a variety of industries including business, manufacturing, education, health, and governance. However, there is a common denominator irrespective of the application of artificial intelligence (AI) i.e., affective or emotional intelligence (EI) of AI systems. This paper aims to discuss the integration of major elements of EI models into artificial emotional intelligence (AEI) systems.
Design/Methodology: The paper structure is descriptive. Based on 50 studies examining the areas of AI, EI, and AEI, the paper expands the discussion on the interlinks between AI and EI.
Findings: With the availability of big data, advanced data analytical tools, complex algorithms capable of conducting multivariate analysis, expandable memory, and retention, AI embarks on understanding, learning, and applying human emotions, and attaining emotional intelligence. This study proposes that artificial emotional intelligence can be achieved by simulating the learning mechanisms exhibited by human beings.

Research Implications

The indispensable interface between man and machine makes it pertinent to discuss AI's ability to embrace and internalize human emotions. The study has implications for every industry, especially those that are looking to employ AI tools to assist or replace human counterparts.

Originality

Based on the most renowned model of emotional intelligence presented by Goleman, this study proposes a rudimentary EI model for outlining the basic facets of AEI systems. The study contributes to the literature examining the crossover between AI technologies, emotions, and learning.

Keywords: *artificial intelligence, emotional intelligence, artificial emotional intelligence, learning.*

Paper type: Research Paper

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INTRODUCTION

There is a deep-rooted association between artificial intelligence (AI) and cognitive psychology. The goal of the former is to think and act like humans while the latter views the human brain as a machine that receives and processes information to perform various tasks (Russell & Norvig, 2010). Considering both the human brain and machine as systems that send, receive, comprehend, and process data, why cannot machines mimic all the other functions of a human brain as well? This question has baffled the scientific community at least since WWII when artificial intelligence proved to be an aid in breaking the German code, determining war strategy, and reshaping the world. While the research in AI encompasses a variety of fields including computer science, linguistics, mathematics, statistics, neuroscience, and cognitive psychology, this paper draws attention to the affective component of artificial intelligence.

The debate about artificial emotional intelligence (AEI) is on the rise given the need for the creation of whole or complete agents. These whole agents signify intelligence across a variety of complex tasks and situations. In a nutshell, an AEI system must possess cognitive as well as affective intelligence, especially if it is to be compared to a human counterpart in terms of intellect (Wang & Baker, 2024; Zhou & Jiang, 2024). The ability to make decisions, and solve problems paired with the uncertainty principle, something all humans are exposed to, must also be simulated in an AI system if it is to be truly called intelligent (Nilsson, 2010; Russell & Norvig, 2010). Thus, exhibiting and responding to, in addition to detecting, and understanding human emotions would count as an integral part of artificial emotional intelligence.

Regardless of AI's ever-expanding capabilities, it still struggles with certain tasks. For instance, AI predictability is lower than that of humans, suggesting uncertainty in monitoring AI actions (Kandul et al, 2023). When it comes to AEI, better control over AI requires a deep inquiry into how and which emotions can be incorporated into AEI systems. While working on AI art, Demmer et al (2023) underscore the need for creating an emotional connection between AI art and human perceivers. In this regard, projecting specific nuanced emotions complementary to the context at hand requires special attention (Demmer et al, 2023; Tariq et al, 2022). Research is also needed to examine the interplay between AI technologies and elements of social psychology. Given the primal human needs of love, affection, and belongingness, AI developers must inculcate behavioral and psychological parameters in AEI systems ensuring effective human-computer interaction (Pentina et al, 2023). The development of holistic AEI models supported by sound theoretical and conceptual frameworks is needed to realize the goal of a realistic and proficient AEI machine (Nalis & Neidhardt, 2023). For developing such AEI systems, this paper proposes that human learning mechanisms can be mirrored in modern-day machine learning tools. While AI systems already rely on approaches such as neural networks, bootstrapping, and reinforcement, this paper aims to draw attention toward emotional learning. The three learning theories that may enable AI's EI (emotional intelligence) learning are classical or respondent conditioning theory (Pavlov, 1927), reinforcement or operant conditioning theory (Skinner, 1958), and social learning theory (Bandura, 1977). In the context of this paper, these theories posit that just like humans, machines may also learn from specific stimuli, outcomes, and behavioral imitation through social interaction. Moreover, for establishing a definite set of emotional behaviors and characteristics to be possessed by AEI, Goleman's EI dimensions are discussed as a benchmark (Goleman, 1995). Based on the earlier EI studies (Mayer & Salovey, 1993), Goleman's work in the field of EI is brief, comprehensive, and scientifically supported.

Research Objectives

To provide a brief introduction to artificial intelligence and related technologies.

To understand the association between artificial intelligence and emotional intelligence.

To discuss and highlight the significance of artificial emotional intelligence.

To propose a set of affective characteristics that an AI system must possess to become an AEI system.

Research Methodology

The research approach adopted by this study is descriptive. Since the purpose of this research is to explore the AI systems' capacity to perceive, understand, and project emotions, the study dives deep into the literature on AI, EI, and AEI. A total of 50 studies are examined for this purpose. By comprehending the dynamics of these fields, this paper proposes five EI characteristics that must be possessed and exhibited by AI systems to establish AEI.

Literature Review

Artificial Intelligence

Artificial intelligence has been defined in terms of rationality and performing functions only humans are capable of. It refers to advancements in computational methods whilst tackling more complex problems at a greater pace. The bottom line remains that artificial intelligence needs to be in congruence with the idea of human intelligence (Berente et al, 2021). AI definitions seem to include multiple perspectives. i.e., a machine is artificially intelligent if it can understand, articulate, and reason just like a human being. On the other hand, AI is also defined as a system that comprehends not only the rational part of human behavior but also the affective and behavioral part, which oftentimes is far from rational. Here a machine may be called intelligent if it passes on both fronts (Russell & Norvig, 2010). Based on this notion, AI has been classified into three areas namely *analytical AI*, which refers to learning from past data, *human-inspired AI* which aims to understand and imitate cognitive functioning and affective behavior of human beings, and *humanized AI* which symbolizes a futuristic AI version that would be sentient and self-conscious (Kaplan & Haenlein, 2019).

Artificial intelligence goes beyond understanding and interacting with human beings. It also mimics and learns from them subsequently giving birth to intelligent machines capable of creative thinking and problem-solving (Zhang & Lu, 2021). According to McCarthy et al (1955), each facet of intelligence exhibited by human beings may be precisely simulated to create an artificially intelligent system. This can be explained through two basic approaches, namely GPS (general problem solver) where the machine tries to imitate human problem-solving tactics, and GTP (geometry theorem prover) where the machine not only imitates but learns and surpasses its human counterpart. The advancement in AI was further accelerated through multiple phases of experimentation and evolution, and by using algorithms to mimic neural networks that constitute the decision process in the human brain. The results were successfully demonstrated by AI successfully playing games like chess and beating human opponents.

The idea of forming neural networks in programmable machines for decision-making comes from the brain's neural network that is governed by neurons. Thus, by simulating artificial neurons, also known as neural elements, one can hope a machine would follow the same pattern of decision-making, problem-approaching, and problem-solving as a human does. This notion of equating human brain neurons to neural elements (artificial neurons) rests on the idea that each neuron in the human brain resembles a logic unit in a computer system. Thus, a neuron that represents a thought/emotion/instinct can be simulated by a computer through neural elements. Together groups of these neural elements fired as inputs and received by other neural element groups as output can constitute *thinking* (Nilsson, 2010; Wang & Baker, 2024). Here a clear distinction can be made between AI systems and machines that may be automatic and programmed but are unable to perceive their surroundings. For instance, a clock, air conditioner, electronic gate, or a television. All these machines perform a given task based on their hardware design and program input. However, they are unable to learn from their surroundings or use existing data to create new ideas. In simple words, such machines cannot think.

To establish if a system is intelligent, the most popular and rudimentary test used is the Turing test (1950). It is comprised of four factors i.e., understanding human language (English), the ability to store or memorize bits of information, the ability to reason and generate new responses, and the capacity to adapt to evolving contexts and circumstances. If a machine passes these four basic thresholds and is indistinguishable from its human counterpart, then it would be termed smart or intelligent. Hence AI technology is an amalgamation of cognition, emotion, machine learning, big data, enhanced storage capacity, communication through natural language, and decision-making through a complex network of neural elements (Zhang & Lu, 2021).

AI Technologies

As all-encompassing as the field of artificial intelligence is, here are some of the AI technologies that are most pertinent in the context of this research.

Big Data

Big data refers to the availability of a mounting amount of data and information (Zhang & Lu, 2021). The term *big* here does not only refer to the volume of data, but also the veracity of data i.e., reliability and dependability of any piece of information. Similarly, the variety of data is also quite extensive including conventional or structured data like words, numbers, and images. Structured data is usually found in the form of official reports, financial statements, or specific databases. Semi-structured data include books, newspapers, demographic, and economic data. Unstructured data extends to newer bits of information accessible through modern technology. These include but are not limited to data on facial recognition, micro-expressions, body language, social media statistics (clicks, posts, comments, likes, subscriptions, ratings, number of views, etc.), and location data. Another aspect of big data is the velocity or speed at which new data is generated. Taking a look at the totality of structured and unstructured data, the high momentum of new data generation is undeniable (Azad et al, 2020; Elgendy & Elragal, 2014). Thus, there is no shortage of data for AI systems to use, understand, dissect, analyze, and predict. Datasets including billions of words, numbers, images, videos, and audio, are at AI's disposal. Exposed to big data, AI systems' ability to learn from what they know grows exponentially (Russell & Norvig, 2010).

With such steady streams of data being generated at an enormous pace, analysis and actionable deciphering of the data is indispensable. Here comes the role of analytics. Data analytics is categorized into four groups. Descriptive analytics provide tools for the rudimentary reporting of data. Diagnostics analytics aid in diagnosing notable problems, patterns, or anomalies in the data. Predictive analytics are used to forecast a future event through simulation and statistical modeling. Prescriptive analytics aim to provide solutions to problems identified in either of the last three stages (Kale et al, 2022). Utilizing all such metrics for big data mining and analysis not only poses serious hardware and power requirements, but also demands the right software tools, expandable memory, and faster computational speeds (Elgendy & Elragal, 2014; Zhang & Lu, 2021).

Machine Learning Algorithms

Handling big data through conventional analysis and techniques is impossible. Given the volume, variety, and velocity of data, it is unfathomable to analyze it under one centralized system. To simplify the analysis, data goes through the steps of extraction, refining, reduction, and mining (Tsai et al, 2015). Data mining is perhaps one of the most critical steps in big data analytics since the patterns identified during the mining phase pave the way for developing actionable strategies.

Large datasets are handled using various algorithms. Algorithms outline specified procedures to perform a computation or solve a problem (Zhang & Lu, 2021). These algorithms are the building blocks for machine learning and artificially intelligent systems. It should be noted here that machine learning algorithms are designed to handle structured as well as unstructured data. Given that AI's goal is to use existing data to learn and improvise, machine learning algorithms may very well deal with data under uncertainty. This points toward a machine that learns to modify the original algorithm or set of instructions based on the newer data it receives, thus exhibiting artificial intelligence.

This brings us to the types of machine learning. Supervised learning is mostly task-driven. The input data is fed to the system to produce desirable target data (Marsland, 2009). Commonly used supervised learning algorithms include linear regression (predicting the target variable through an input variable), logistic regression (establishing categorical or binary classification), neural networks (simulating the functioning of human brain through layers of nodes), C4.5 (predicting an instance based on desirable threshold of attributes for mutually exclusive classes), support vector machine (data classification by establishing hyperplanes or decision boundaries), AdaBoost (improving the accuracy and generalizability of binary classifiers by iterative learning of weak classifiers), k-nearest neighbor (predicting an instance based on the proximity of data points to other available data), Naïve Bayes (data classification by ensuring equality and mutual exclusiveness of all predictors in determining the outcome), decision tree (determining an outcome by splitting decision nodes in a dataset covering all possible outcomes) and random forest (determining the outcome by combining the output of multiple decision trees) (Delua, 2021; Wu & Kumar, 2009).

Conversely, unsupervised learning requires the algorithm to determine the output based on certain patterns, clustering, or similarities. Without the target data, unsupervised learning denotes data classification without human input. Thus, it rests upon the notion of probabilistic modeling (Marsland, 2009). Examples of unsupervised algorithms include k-means (data clustering based on intra-group homogeneity and intergroup heterogeneity determined by distance from the cluster's centroid), hierarchical clustering (a bottom-up approach to unite several groupings under one cluster based on similarity), Apriori (pattern recognition through a minimum number of prior occurrences), expectation maximization (treating incomplete datasets through iterations based on maximum likelihood), and dimensionality reduction (reducing the number of dimensions in a dataset by classifying data based on inter-component variance) (Delua, 2021; Wu & Kumar, 2009).

Reinforcement learning is another type of machine learning that is based on trial and error. Such a system adopts both supervised and unsupervised learning mechanisms to determine the target output. It is prompted each time it makes an error. The machine then tends to modify its behavior based on the new prompt. A similar approach is evolutionary learning which signifies systems' organic evolution to find the best data fit for a model. Derived from evolutionary biology, the idea behind evolutionary machine learning is to train a machine to learn and survive on its own based on the data, trial and error approach, as well as human prompts (Marsland, 2009).

Robotics

Another worth discussing technology of AI is robotics which aims to study the process of design, development, and functioning of robots. Robotic technology ranges from programmable robots that perform specific step-by-step functions to ones that are equipped with sensors for perceiving their physical environment. Intelligent robots may be considered an extension of sensory robots. Such robots may have visual, auditory, and even tactile sensors to enhance human-computer interaction and perform desired functions more effectively (Zhang & Lu, 2021). Also known as embodied AI, these robots have abilities like object detection, sound, motion, and gesture recognition. Research shows that embodied AI is more sensitive to environmental cues for learning and response relative to disembodied AI (Harris et al, 2024).

Equipping robots with AI through machine learning technologies has resulted in breakthroughs across healthcare, governmental, military, corporate, and business/economic sectors. Like other machines, robots utilize various algorithms to perform tasks pertaining to production and manufacturing, service automation, logistics, navigation and traffic management, quality inspections, disaster management, crime control, and surveillance (Ing & Grossman, 2023; Soori et al, 2023).

Emotional Intelligence

Emotional intelligence refers to the ability of emotion recognition and regulation. It involves the attributes of both emotional displays as well as emotional inhibition. It is not confined to rudimentary social skills but is necessary for intellectual processing which is driven by the brain's neural networks (Mayer & Salovey, 1993). Goleman (1995) discusses eight primary emotions experienced and projected by humans. These are anger, sadness, fear, enjoyment, love, surprise, disgust, and shame. Goleman (1995) goes on to define each emotional state in terms of its physiological symptoms.

For instance, anger raises one's heart rate, whereas fear puts the body into a state of alert. Happiness and love produce feelings of contentment and positivity, while sadness drains one's physical energy and enthusiasm. Moreover, disgust and surprise are shown through certain facial expressions. Figure 1 highlights some physiological and psychological pointers that indicate different emotions.

Figure 1

Anger	• Verbal and physical aggression (Whiteside & Abramowitz, 2004), irritation, frustration, muscular tension, varying skin conductance levels (Deffenbacher et al, 1996), elevated levels of blood pressure and heart rate (Goleman, 1995) and eye movement (Rodger et al, 2023).
Sadness	• Elevated or reduced heart rate, feelings of guilt and failure, tears, varying skin conductance levels (Shirai & Suzuki, 2017), facial expressions like lip stretching, frowning through lower brow raise (Tsikandilakis et al, 2024) varying eye movement (Rodger et al, 2023) and loss of energy (Goleman, 1995).
Fear	• Change in heart rate, varying skin conductance levels (Taschereau-Dumouchel et al, 2021), physical attentiveness, body freeze (Goleman, 1995), voice, facial expressions (Marsh et al, 2007), and varying eye movement (Rodger et al, 2023).
Enjoyment	• Smiling (Abdullah et al, 2015), Physical energy and enthusiasm (Goleman, 1995), positive affect (Diener et al, 2020), and varying eye movement (Rodger et al, 2023).
Love	• Muscular relaxation, physical calm and contentment (Goleman, 1995), Body language indicators like raised shoulders, touching, physical closeness; voice indicators like baby talk, and facial expressions like glistening eyes, smiling, and flushing (Shaver et al, 1996).
Surprise	• Facial expressions like eyebrow lift (Goleman, 1995), verbal report of surprise (Meyer et al, 1997), changing eye movement (Rodger et al, 2023), pupil dilation, elevated skin conductance and increased heart rate (Reisenzein et al, 2017).
Disgust	• Facial expressions like upper lip curling, nose wrinkling (Goleman, 1995), eye movement (Rodger et al, 2023), feeling sickness, repulsion and pity (Gutierrez et al, 2012).
Shame	• Silence, negative self-evaluation, nervous laughter, giggling, change in voice pitch, blushing, sweating, gaze aversion, non-similing, biting lower lip, withdrawal (Maire et al, 2022).

Measured as emotional quotient (EQ), EI is an integral part of intellect (Beasley, 1987). Goleman (1995) explains the importance of EI by discussing the effects of the absence of the amygdala (part of the brain responsible for processing and regulating emotions) in the brain. The amygdala is a key determinant in shaping not only basic social interactions but also survival instincts during a toxic social encounter. For instance, looking for emotional cues like a smile or frown in an uncertain social setting points to the indispensability of the affective amygdala in social discourse. It should also be noted that the amygdala is not only responsible for regulating emotions but also for the correct deciphering of emotional cues communicated through facial expressions or body language. This leads to the formation of a neural network in society, resulting in a communication-feedback loop (Goleman, 2006). Thus, without this crucial cog, the machine we call the human brain would not be optimally functional. Goleman (1995) calls the lack of emotionality in the absence of the amygdala, affective blindness.

Goleman (1995) emphasizes that despite having a high intelligence quotient (IQ), one can make the dumbest of decisions. He explains this through the examples of numerous allegedly smart individuals who scored high on IQ tests but managed to make completely erratic and irrational decisions i.e., suicide, and murder. This points to the need for a well-rounded intelligence that covers both cognitive as well as affective aspects of intelligence. Some of these include control over impulses, emotional adaptability, empathy, and interactive skills (Matthews et al, 2004).

Literature explores numerous dimensions of EI. These dimensions typically fall under two categories, i.e., ability EI and trait EI. The former refers to the mere understanding of emotions and how they are regulated. The latter discusses individual behavior in specific contexts where EI is needed (Petrides & Furnham, 2000). Contemporary research in EI also highlights the mixed EI models that combine and extend the scope of ability and trait EI (O'Connor et al, 2019). Though there remains a debate as to whether emotional intelligence is manifested through ability or trait, all mainstream schools of thought concur that emotional intelligence is overall an amalgamation of both and is a pivotal part of intellect pertaining to effective social functioning (Kanesan & Fauzan, 2019).

Goleman (1995) put forward five facets of emotional intelligence. According to him, an emotionally intelligent person is self-aware, i.e., they are well-informed about the emotions they experience, can regulate different emotions like anger or sadness and do not get carried away, can self-motivate to stay on track, can exercise empathy by recognizing others' emotions, and lastly can function well in social settings, through effective interpersonal and people skills. Other facets of emotional intelligence include emotional labeling ability (Drigas & Papoutsi, 2018), emotional appraisal, emotional comprehension, and emotional reflection (Mayer & Salovey, 1997), assertiveness, independence, problem-solving ability, self-actualization, self-tolerance, and optimism (Bar-On, 1997; 2000).

In this study, we are taking the emotional intelligence model proposed by Goleman (1995; 1999). The reason behind choosing Goleman's model is that it builds upon and refines the previous notable works in the field of EI (Mayer & Salovey, 1993). Goleman discusses EI as both ability and trait models (Kanesan & Fauzan, 2019), and looks at EI from both cognitive and affective perspectives, acknowledging the intricate relationships among cognition, affect, logic, and reasoning. His work shows that EQ is in fact part of IQ. Moreover, Goleman approaches EI from social as well as scientific standpoints, strengthening its need as part of the intelligence construct (Goleman, 1995; 1999; 2006).

Artificial Emotional Intelligence

A significant part of the scientific community advises against developing holistic intelligence systems like AEIs. The skepticism comes from the fear of being overcome by AI or superintelligence (Sparrow, 2023). AI remains emotionally weak and incapable in the face of the complexities of human life (Ruckenstein, 2023). Thus, the integration of EI and AI seems all the more necessary. By equipping AI with EI, threats like human extinction at the hands of cold-blooded, calculated AI may not see the light of day.

Despite notable leaps in the AI field, it has a long way to go before attaining human-like attributes like emotional intelligence. Currently, problems including AI hallucination, inaccurate inferencing, system bias, and decision accountability are encountered in AEI systems (Corvite et al, 2023; Podoletz, 2022). Users tend not to trust AI when it comes to subjective decision-making requiring intuition. Specifically, emotional AI has received user skepticism due to privacy concerns and ineffectiveness across varying social contexts (Behn et al, 2024). AI's apathy toward human privacy and its wrongful use are also cause for concern when employing AEI (Roemmich et al, 2023). At this point, AI engineers are urged to build a strong understanding of complex human emotions and build users' trust through transparency in data acquisition and usage mechanisms. This can be achieved by modeling AEI systems based on different cross-cultural ethical philosophies (Mantello & Ho, 2023). Irrespective of these limitations, AEI has become an integral need for organizations. For businesses, algorithms configure users' preferences based on the number of clicks, likes, and shares. Similarly, users' gender, emotional state, language, accent, and location are also used by AEI to provide the most customized service experience online (Ho et al, 2023). Customers expect AI to be emotionally responsive to their needs. While interacting with AEI systems and bots, a lack of appropriate facial expressions communicating the right emotion at the right time may lead to customer dissatisfaction. The utility of AEI in process-focused services is especially important where users seek a holistic experience from AEI, covering both the functional and emotional aspects of its performance (Zhang et al, 2024). Business benefits of AEI extend to cost saving, efficient information and feedback systems, and improved employee performance through affect surveillance (Mantello et al, 2023). In healthcare, AEI performs tasks like emotion detection which is a vital part of the treatment of different psychological and neurological diseases including Alzheimer's and, Parkinson's disease, dyslexia, autism, anxiety, and depression (Khare et al, 2024).

AEI can be instrumental in customizing the educational content according to students' emotional prompts (Keshishi & Hack, 2023). Accordingly, it may assist in teaching, research, examination, and data analysis (Dolunay & Temel, 2024). It is also more efficient in coaching, and mentoring, by ensuring higher coachee engagement, convenience, and ultimately goal attainment (Terblanche et al, 2022).

Borrowing from psychology, the classical or respondent conditioning theory (Pavlov, 1927), operant conditioning or reinforcement theory (Skinner, 1958), and social learning theory (Bandura, 1977) may provide a foundation for AI's emotional learning. Respondent conditioning posits that combining an unconditioned with a conditioned stimulus would elicit the desired response. This concept of learning is mirrored in machine learning using semi-supervised and ultimately unsupervised learning algorithms. For instance, bootstrapping and content classification. The operant conditioning or reinforcement theory states that behavior is determined by repeated or reinforced outcomes. This is perhaps most incorporated in supervised machine learning algorithms where the outcome is fed into the system as input to determine a predictable response. Examples include spam detection and biometric data management. Thus, both respondent and operant conditioning techniques are embedded in machine learning algorithms. It can be argued here that both the above concepts largely fall under deterministic rather than stochastic AI. Conversely, when it comes to emotions and affective responses, the world becomes even more uncertain, random, and subjective. Thus, in addition to learning from stimulus and outcome of behavior, machines must also incorporate the social learning approach that argues that learning occurs through observation and imitation of fellow social beings (Bandura, 1977). Combining the above three learning approaches would help build a holistic AEI that embraces the deterministic (predictable) as well as the stochastic (random) learning mechanisms.

As mentioned earlier, there are eight basic forms of emotions namely anger, sadness, fear, enjoyment, love, surprise, disgust, and shame (Goleman, 1995). These emotions are far too deep and complicated to be treated as isolated (Schuller & Schuller, 2018). Thus, the goal of any machine aiming to become artificially emotionally intelligent must be able to encapsulate all these emotions in terms of their potential categories, antecedents, and outcomes. For instance, happiness emotion can be exhibited by a variety of factors, including a smile, its duration, its specific type, and the specific context in which a smile is used to convey happiness. A smile in a specific situation may be nothing more than a smirk or a sign of nervousness which comes under the category of fear instead of happiness. Similarly, there are numerous ways in which anger, sadness, surprise, or disgust are manifested. An AEI system must possess the ability to differentiate between all these emotions and respond accordingly. The good news is that today big data has made it possible for machines and smart systems to access the kind of data necessary for learning EI. Whether it is verbal, written, visual, or auditory data, machines have multiple vantage points to detect and dissect each of the aforementioned emotions. However, the bad news remains the subjective nature of emotional display due to which a cue can be misread (Pietikäinen & Silvén, 2021). For instance, Elyoseph et al (2024) found a difference in the proficiency of ChatGPT 4 and Google's Bard when exposed to certain textual and visual prompts. The former having been trained on a more emotionally varied dataset displayed a higher emotional awareness than the latter. Wang et al (2024) suggest building an emotional dialogue system based on users' personality types. Such a system would be more malleable in the face of user diversity.

Looking from the vantage point of an AEI system, all the emotions and their indicators mentioned in Figure 1 must be thoroughly embedded and understood by an AI system aiming to score high on EQ tests. In addition to this, further sub-categorization of certain emotional cues is vital for an effective AEI system functioning. For instance, differentiating between types of smiles, expressions of anger, stress (distinguishing eustress from distress), exhaustion (physical vs emotional), and forms of happiness must be learned by AEI. Similarly, AEI must be well versed in detecting pointers of social awkwardness, varying sense of humor, and other forms of emotional display across different cultures and languages. In this regard, data on the user's physical state like posture, gestures, expressions, and speech are evaluated for inference (Khare et al, 2024).

One of the most notable initiatives in AEI was the development of a sociable robot Kismet. This robot was also built for social interactions by allowing it to pick social, emotional, and physical cues from its surroundings and learn to respond accordingly. Kismet largely depends on the use of visual and auditory data to detect emotions (Breazeal, 2003). Tools like Siri and Cortana also mainly rely on auditory input. For visual data, a learning focal point algorithm is proposed to efficiently detect isolated stimuli from an image typically a face, followed by the classification of different images based on the emotions they project (Sakhi et al, 2024). Though today's AI has the ability to recognize and even generate certain emotions, it still struggles with the task of emotion augmentation (Schuller & Schuller, 2018). While AI systems rely mostly on textual and visual stimuli to detect the nature of emotions, research on emotion augmentation also discusses methods like tactile stimulation to precisely detect and enhance the experience of emotions (Tsetserukou & Neviarouskaya, 2012). For this purpose, the user's physiological data including respiration, temperature, galvanic skin response, and electrocardiogram is also used as stimuli by AEI (Khare et al, 2024).

Similarly, the use of avatars to simulate real-world interactions is also in the pipeline and may even see the light of day with initiatives like Meta's virtual reality. It should be noted here that an ideal AEI system would be the one that can convince a human that the former has intentionality, beliefs, feelings, and values of its own (Breazeal & Scasselatti, 1999). However, research suggests that humans remain less receptive to AI emotional displays due to factors like uncanny valley (Harris et al, 2024).

Across the textual data, sentiment analysis is performed to detect the nature of emotions. For emotion detection of specific emotions in text, social media comments, blogs, books, or any other written material, different approaches are used including emotion vocabulary where the machine learns a set of words denoting one specific emotion, based on the context of their usage. Another method of determining emotional expression from a body of text is negation handling where the words *no* or *not* point to a specific emotion. These when coupled with certain adjectives like *incredibly, extremely, unbelievably, or madly*, communicate the intensity of the said emotion. Furthermore, the process of topic modeling where examining the text themes and frequency of certain phrases helps identify the context in which the emotions are displayed (Adikari et al, 2021). The use of emoticons, punctuation marks, or a specific writing style also communicates the emotional undertone of a body of text to AEI (Taherdoost & Madanchian, 2023). Moreover, textual data analysis also highlights the causes and triggers of various emotions. Textual analysis through deep learning algorithms reveals a myriad of emotional cues facilitating effective human-computer interaction (Li et al, 2024).

Moving forward, it is pertinent to establish AEI attributes based on a specific EI model that an AI aims to incorporate (Adikari et al, 2021). As discussed earlier, Goleman (1995; 1999) proposed five dimensions of EI. These dimensions along with their brief description and possible synchronization with AI are depicted in Table 1.

Table 1.

		Description	AEI	Literature
1.	**Self-Awareness**	Awareness about one's thoughts, feelings, behaviors, intuitions, and limitations.	• AEI's imitation of the brain's limbic system using memory, machine learning, and knowledge retention. • Learnable emotions based on constructivist philosophy. • Appraisal of specific cognitive or affective stimuli. • Appraisal of the machine's own functioning and driving algorithms and how they are modified and adapted. • Building perception about the nature and	(Ho, 2022; Jimenez, 2018; Martinez-Miranda & Aldea, 2005; Zhang & Fabus, 2022)

			source of stimuli being received.	
2.	**Self-Regulation**	Exhibiting conscientiousness, preciseness, self-control, adaptability, and ability to evolve with change.	• Autonomous decision-making through environmental adaptability. • Provision of limited training data to facilitate unsupervised machine learning. • Affective computing using big data. • Replacing heuristics with data-driven decision-making.	(Beck & Libert, 2017; Cristianini et al, 2023; Ho, 2022; Martinez-Miranda & Aldea, 2005; Shank et al, 2019)
3.	**Self-Motivation**	Possessing a sense of initiative, drive, commitment, and intrinsic motivation.	• Steering AI toward emotional learning through a path-goal approach. • Using supervised learning algorithms for predicting a goal by adding specific affective stimuli in the path. • Using the right affective stimuli for creating a model behavior.	(Cristianini et al, 2023; Martinez-Miranda & Aldea, 2005)
4.	**Empathy**	Ability to understand an issue from multiple standpoints, predict others' needs, and reciprocate as/when needed.	• Distinguishing and understanding emotions across cultures and contexts. • Ability to understand and empathize with others' life situations without bias and preconceived notions. • Acknowledgement of uncertainty and change in any context.	(Beck & Libert, 2017; Ho, 2022; Shank et al, 2019)

5	**Social Skills**	Ability to detect conversational patterns, effectively communicate, engage in discussion, develop mutual understanding, and influence and persuade others through dialogue.	• Ability to engage in conversations while reciprocating the required emotions. • Establishing causality among cognition, affect, and subsequent reasoning. • Enabling imitation of human behavior through multiagent learning. • Incorporating human-inspired AI by building humanlike robots, whilst strengthening the perception of a real interaction.	(Ho, 2022; Kaplan & Haenlein, 2019; Prentice et al, 2020; Shank et al, 2019; Zhang & Fabus, 2022)

Designing such an elaborate AEI system covering the EI attributes mentioned in Table 1 would require highly specialized and custom-built tools of machine learning. The rationale behind building a comprehensive AEI is to enable a self-sustaining mechanism that drives the system's EI learning by taking both feedforward or input from the environment and based on reinforcement (trial and error), and feedback, it modifies behavior just like a human does. This notion of behaviorism is very much consistent with how humans learn (Zhang & Fabus, 2022). Similarly, the frequent interaction between machines and human beings allows for the collection, analysis, and imitation of vast and diverse amounts of data. AI may very well be a lot better than us at learning given its information processing speed, memory, and retention. Furthermore, no human has been able to collect, process, analyze, and decipher the likes of big data, as fast and comprehensively as computers and AI systems do.

Discussion and Future Research Avenues

This paper focused on discussing the basics of artificial intelligence and its synchronization with the affective/emotional component of human society. While apps like ChatGPT, Chatbot, Siri, Cortana, and Bard have proven their astounding ability to perform certain tasks better and faster than us, there remains a gap in such interactions when it comes to emotional display and reciprocation (Pietikäinen & Silvén, 2021). For instance, ChatGPT has outperformed its human counterparts in fields like engineering, medicine, business, and law (Varanasi, 2023). Additionally, many AI systems have embarked upon and successfully completed tasks that no one thought machines would ever be able to perform. These include painting, poetry, music, and miscellaneous artistic endeavors. But the fact remains that despite all this, machines severely lack exhibiting EI.

A general expectation from an advanced AI machine is that it would be sentient, self-conscious, and even able to confront or disagree with its human counterpart. Typical examples of such AI have been demonstrated in movies like 2001; A Space Odyssey, Ex Machina, Eagle Eye, and Megan. The catastrophic consequences of AI attaining human-like thinking capability are discussed not only in fiction but also by scholars including Bostrom (2014), Russel (2019), and Gawdat (2021). Contemporaries like Elon Musk and Stephen Hawking have also warned against the repercussions of AI advancement. Concerns regarding Moore's law (Moore, 1965) and the pace of expanding computational speeds yet again point toward the need to regulate all aspects of AI technologies including emotions. Given the apprehensions surrounding AI's advancing abilities, it becomes even more vital to steer AI in the right direction by introducing just the right EI elements and clearly defining its parameters. In a nutshell, humanity needs to control and regulate the AI rather than being controlled and regulated by the AI.

This paper is written from the perspective of a social scientist and may have sidelined the technical aspects regarding the development and execution of AEI systems. Future studies may extend this work toward empirical research. This study sticks to the basics of AI to cultivate a basic knowledge about the subject. Similarly, aspects of EI also cover the most basic of emotions and EI dimensions. Future research should explore each aspect of EI in-depth, while in conjunction with AI. Lastly, the study remains objective and does not elaborate on the pros and cons of AI and AEI applications. Future papers may address the ethical, spiritual, and societal impact of AI and AEI across different contexts and cultures.

Practical Implications

This study has several practical implications. Firstly, facilitating smooth human-AI communication is vital for businesses. Effective AEI can be quite fruitful for service providers in responding to customer demands in addition to warding off their negative emotional experiences. It can also be used for effective market research, targeting the most suitable markets for launching different products, and understanding consumer and market behavior. AEI can be of tremendous assistance in healthcare by understanding patients' emotional states. In education, lesson and learning plans can be customized based on the mental and emotional states of students. It can also enhance cross-cultural communication by developing cultural sensitivity toward different groups. As AI attains emotional intelligence, it would deal better with the ethical and legal constraints it is currently bound by.

Conclusion

The aim of this paper was to highlight both the potential challenges as well as opportunities in making AI emotionally responsive and intelligent. While major landmarks have been achieved in this area, AI systems still lag in internalizing and exhibiting the emotions as felt and displayed by humans. This research points out that AI systems can be modeled based on human learning approaches. A comprehensive EI model by Goleman (1995) is at our disposal to inculcate the necessary affective elements in the AI machines, transforming them into AEI machines.

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