Unleashing Trends of Artificial Emotional Intelligence: A Bibliometric Analysis Using VOS Viewer

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ABSTRACT

Artificial Emotional Intelligence (AEI), an interdisciplinary field combining artificial intelligence and cognitive emotion, has gained significant attention in recent years due to its potential applications in healthcare, education, and human-computer interaction. This study conducts a comprehensive bibliometric analysis to unleash trends, research hotspots, and collaborative networks within AEI using VOSviewer Software (version 1.6.20). By analyzing data from Scopus database with subsequent advanced query: TITLE-ABS-KEY (“Artificial” AND “Emotional intelligence”) that published in the period 2000 to 2025, key insights are derived from co-authorship networks, keyword co-occurrence patterns, and citation analysis. The data were extracted in November 2024, and the choices are restricted to journal papers that have reached the final stage of publication. A search using these keywords yielded over 656 documents. Following the screening process, a total of 392 documents were retained. A total of 351 papers were selected for further investigation after the manual screening process performed. This research identifies influential authors, institutions, and countries contributing to AEI's growth, along with thematic clusters that define the field's evolution. A publication growth in AEI gradually increase but a spike increase in publication was found in 2024. The findings reveal emerging themes such as multimodal emotion recognition and its applications in real-world contexts. The study provides valuable insights into the current landscape and future directions of AEI, serving as a roadmap for researchers and practitioners in this rapidly evolving domain.

Keywords: Emotional Intelligence, Artificial Intelligence, Artificial Emotional Intelligence, Bibliometric Analysis, VOS viewer

INTRODUCTION

“Irish writer John Connolly encapsulated the essence of humanity in his words: “The essence of humanity is to feel another’s pain as our own and act to ease it. Compassion is noble, empathy is beautiful, and forgiveness is graceful.” This sentiment resonates with Meryl Streep’s observation that “The great gift of humans is empathy; we all feel a mysterious connection to each other.” Throughout history, emotional intelligence is defined as the ability to understand and manage our emotions while empathizing and communicating with others (Goleman 2012; Liu-Thompkins et al. 2022; Picard 1995) has been regarded as a defining human trait, distinguishing us from animals and machines.

The notion that emotional intelligence is uniquely human is being contested by the emergence of Artificial Emotional Intelligence (AEI), a novel class of Artificial Intelligence (AI) systems that mimic human emotional intelligence by sensing, interpreting, and responding to human emotions (Pervez et al., 2024; Podoletz, 2022). According to Pervez et al. (2024), *sensing* involves data collection from sources like text, speech, facial expressions, physiological signals, and body language to infer a user's emotional state. Meanwhile, *interpreting* refers to utilizing machine learning algorithms and contextual models to process the collected data and comprehend emotions. *Responding* signifies the system's ability to adapt its behavior based on interpreted emotions, such as adjusting outputs or interaction styles for an emotionally responsive experience.

AEI represents a transformative frontier in the intersection of technology and human interaction, where machines are increasingly equipped to understand and respond to human emotions. The term "affective computing" was first coined by Rosalind Picard in her seminal book published in 1997, which laid the groundwork for integrating emotional intelligence into computational systems. Since then, AEI has evolved significantly, leveraging advances in machine learning, natural language processing, and computer vision to enhance human-machine interactions. Additionally, AEI has seen exponential growth in research and applications due to advancements in neural networks and sensor technologies. The ability of machines to process emotional cues from multiple modalities such as facial expressions, vocal tone, body language, and physiological signals has opened new avenues for human-computer interaction, making technology more intuitive and empathetic, This emerging field draws from advancements of systems that recognize emotional cues and stimulate emotional responses. As the market for AEI continues to expand, projected to grow from approximately $3.745 billion in 2024 to $7.003 billion by 2029, with a compound annual growth rate (CAGR) of 13.34%, the implications for various sectors, including customer service, healthcare, and education, are profound (Research and Markets, 2024).

Recent studies have underscored significant advancements in emotion recognition technologies, particularly those leveraging deep learning algorithms and multimodal data to improve the accuracy of emotion detection (Jale Narimisaei et al., 2024). A comprehensive review published in 2024 highlighted the integration of emotional intelligence into AI systems, focusing not only on the remarkable progress made but also the persistent challenges faced in recognizing and appropriately responding to human emotions (Mosleh et al., 2024; Pervez et al., 2024; Olider et al, 2024). This research emphasized the critical role of contextual information and individual traits in improving emotion understanding. These developments are crucial as emotion recognition technology holds vast potential across diverse applications, ranging from healthcare and education to customer service and mental health, where more accurate and empathetic AI systems could significantly improve human-machine interaction and decision-making processes.

In a similar vein, recent research highlights the transformative potential of AEI across various domains. For instance, in healthcare, AEI-powered systems are being used to monitor mental health by detecting emotional states like stress or anxiety from physiological data (Levin et al., 2024). In education, adaptive learning platforms use emotion recognition to tailor content based on students' emotional engagement (Shomoye & Zhao, 2024). Moreover, customer service has benefited from chatbots and virtual assistants capable of delivering emotionally sensitive responses, improving user satisfaction (Juipa et al., 2024; Eswar Sudhan et al., 2024; Pawlik et al., 2022).

Recent bibliometric analyses utilizing tools like VOSviewer have illuminated the rapid growth of scholarly publications on AEI, highlighting significant trends and thematic clusters within the research landscape. For instance, studies have shown a marked increase in publications related to AEI and its applications in leadership and organizational behavior over the past decade (Ojha et al., 2024; Yousaf et al., 2021). This bibliometric analysis not only identifies key authors and influential papers but also reveals gaps in current research that warrant further exploration. As AEI technologies evolve, understanding these trends through systematic analysis becomes essential for guiding future research directions and applications in real-world scenarios (Hamouche et al., 2023).

Given the rapid advancements in emotion recognition technologies and the growing integration of emotional intelligence into AI systems, this study aims to explore the following research questions.

RQ1: What are the most influential journals, authors, countries, and research papers in the field?

RQ2: What are the key emerging research trends related to AEI that could open directions to unexplored avenues of research in this field?

RQ3: What are the most researched topics that have been studied with the greatest frequency and are currently attracting the most attention?

Additionally, this study leverages bibliometric analysis using VOSviewer to explore the latest research trajectories, innovations, and interdisciplinary applications in AEI. By examining publication trends, keyword co-occurrences, and collaborative networks, the research aims to map the intellectual landscape of AEI and provide insights into its future directions. Through this, the study seeks to guide stakeholders in academia, industry, and policy in harnessing the transformative potential of AEI.

LITERATURE REVIEW

Artificial Emotional Intelligence (AEI)

Emotional intelligence (EI) has become a focal point in psychological research, highlighting the importance of emotions in both personal and professional contexts. As noted by Salovey and Mayer (1990), EI has gained substantial recognition among psychologists and researchers over the past few decades. It is defined as the skills that enable us to recognize, manage, and effectively communicate our own emotions, as well as understand the emotions of others (Segal, 2008). In essence, EI encompasses the ability to perceive, express, understand, and manage emotions effectively.

On the other hand, scientists and engineers have been continuously studying artificial intelligence (AI) for over 65 years. AI research has achieved significant milestones in both theoretical studies and practical applications (Jiang et al., 2022). The underlying idea is that machines created by humans can perform tasks beyond manual labor and develop intelligence similar to humans. AI is generally defined as enabling machines to perform tasks that typically require human intelligence (Jiang et al., 2022). Although AI has been described in many ways, its core is widely understood to simulate, extend, and expand human intelligence. The rapid growth of AI beyond human capabilities has sparked a new wave of discussions about its potential impact on human society. For example, the integration of AI with emotional intelligence, known as artificial emotional intelligence, is transforming human-computer interactions.

Picard (1995) first introduced the concept of affective computing, which involves using computers to recognize and mimic human emotions. He expanded on this idea in 2000, suggesting that computers could be designed with systems to understand human emotions during interactions. Further, artificial emotional intelligence (AEI) is frequently known as affective computing, is growing quickly due to advancements in AI (Ong et al., 2021). AEI is about developing AI and machines that can detect and respond to emotions (Caruelle et al., 2022). This involves using sensors to capture facial expressions and body signals related to emotions, then recognizing these signals to understand human feelings and provide suitable feedback. Over the past decade, many studies have shown the benefits of interactions between humans and computers or robots.

Given the rapid development of AI technologies, it is now crucial to explore the trends of Artificial Emotional Intelligence (AEI) by integrating interdisciplinary knowledge about its technological foundations, applications, and future directions.

Historical Evolution of AEI

Since Picard introduced the concept of affective computing in 1995, AEI has evolved from a skeptical idea to a respected field that integrates advanced technologies for improved emotion recognition across various domains. Despite challenges such as bias, data collection, and standardization, future research focuses on creating culturally adaptive and privacy-preserving AEI applications. Initially, the idea of integrating emotions into computing faced skepticism and was even ridiculed, with critics considering it contradictory to the nature of computing (Hollnagel, 2003; Picard, 2010). Traditional peer-reviewed journals were hesitant to publish on the subject (Picard, 2010), but the widespread availability of textual data since the mid-2000s, driven by the rise of smartphones, accelerated research in natural language processing (Shreetim, 2024). During this period, affective computing research focused on analyzing facial expressions, body gestures, and sentiment analysis, as well as detecting emotional states through physiological signals like skin conductance and heart rate variability (Batrinca

& Treleaven, 2015; Pantic & Patras, 2006; Zhou et al., 2011). Picard (2010) reflected on this evolution in the inaugural issue of *IEEE Transactions on Affective Computing,* describing how the field progressed "from laughter to IEEE," signaling its growing acceptance.

Modalities in Contemporary AEI

After 2010, researchers have been exploring different ways to improve systems that understand emotions. One of these methods is using Natural Language Processing (NLP) for affective computing. NLP is a part of machine learning that helps computers understand human language. It involves collecting, processing, and analyzing text to help machines understand and generate language (Nijhawan et al. 2022). In the field of emotion understanding, NLP is mainly used for sentiment analysis. This means analyzing spoken or written language to detect emotions and figure out how people feel (Ahmadi & Hammond 2023; Wang et al., 2023; Bilquise et al., 2022). Sentiment analysis is important in areas like social media advertising, political opinions, and understanding customer feedback (Nandwani & Verma, 2021). It helps computers study opinions and emotions expressed in texts about specific topics.

The inherent ambiguity and complexity of human language pose substantial challenges for NLP, as understanding contextual nuances is critical for accurate interpretation (Nijhawan et al., 2022). For example, processing unstructured and "noisy" text from social media is particularly difficult due to the frequent use of abbreviations, misspellings, colloquialisms, and emoticons, which can significantly reduce model accuracy (Bilquise et al., 2022). Additionally, NLP models often struggle to grasp subtleties such as sarcasm and cultural references, further complicating their ability to interpret language effectively (Leonidas Boutsikaris & Spyros Polykalas, 2024). Despite the promising advancements in large language models like ChatGPT, which show potential for improving emotional detection and response capabilities, the intrinsic ambiguity of human language combined with its capacity for multiple interpretations remains a fundamental limitation. This challenge underscores the difficulty of achieving true empathetic understanding in AEI systems.

Facial expression recognition is another key modality in affective computing. This technology analyzes facial muscle movements to identify expressions, which is crucial for understanding emotions and social cues (Krumhuber et al., 2023). It aids behavioral scientists and psychologists in studying emotional responses, helps medical professionals monitor patient distress, enhances security systems by detecting suspicious behaviors, and improves deception detection by analyzing micro-expressions (Dakalbab et al., 2022; Jardine et al., 2022; Podoletz, 2022). This involves collecting data by tracking facial points across sequences of images to measure changes in expressions. Facial recognition technology began being used in affective computing in 2006, initially focusing on emotion recognition from frontal facial images (Pantic & Patras, 2006). The introduction of deep neural networks has significantly improved emotion recognition by enabling the learning of expressive features and capturing various levels of abstraction, thus enhancing accuracy (Krumhuber et al., 2023).

A significant challenge in the domain of facial expression recognition is the cultural variability of emotional expressions. Research by Cordaro et al. (2019) highlights substantial differences between cultures, with Eastern cultures typically exhibiting more subdued expressions and Western cultures displaying more pronounced ones. This cultural disparity poses a substantial obstacle for AEI systems, as a lack of cultural sensitivity can lead to issues of trust, diminished accuracy, and reduced effectiveness (Cordaro et al., 2019).

Another modality in AEI involves the use of physiological body sensors for affective computing. These sensors collect and analyze physiological signals to predict users' emotional states in real-time. They utilize measures such as skin conductance response (SCR), facial electromyography (EMG), and electroencephalography (EEG) to differentiate basic emotions and estimate affective states (Flynn et al., 2023). Skin conductance response (SCR), which reflects emotional arousal through sweat gland activity, is applied in clinical healthcare and physiological monitoring (Bari et al., 2020). EEG captures brain activity related to the limbic system, is crucial in human-computer interaction, medical diagnostics, and military applications. Furthermore, EEG has shown effectiveness in emotion recognition, particularly in response to stimuli like music (Liu et al., 2021).

Challenges in this modality include the scarcity of research on emotion classification using virtual reality, which may elicit more intense emotional responses compared to traditional stimuli (Suhaimi et al., 2020). here is a pressing need for accurate and multifunctional sensors capable of capturing a wide range of physiological signals simultaneously. Addressing these challenges requires more comprehensive representations of affective body language and access to high-quality labeled and unlabeled data (Asiain et al., 2022).

Multimodal affective computing integrates multiple aforementioned modalities, such as facial expressions, physiological signals, and sentiment analysis, to recognize human emotions (Chen et al., 2024). This approach gathers data from various sources, including cameras for facial expressions, physiological sensors for emotional changes, and dialogue interactions for linguistic expressions. However, building effective multimodal systems is challenging due to the complexity of integrating computer vision, audio processing, natural language processing, and psychological insights (Chen et al., 2024). AEI extends beyond the technical focus of affective computing by addressing the interaction between technology, human users, societal norms, and ethical considerations. While affective computing emphasizes multimodal technologies, AEI broadens this perspective to function as a socio-technical system that examines the interplay between technological and human elements across diverse applications. Chen et al. (2024) frame AEI as a socio-technical system that bridges these dimensions effectively.

Mapping the Landscape of AEI Applications

Continuous advancements in AI are rapidly enhancing the ability of systems to detect, interpret, and respond to a variety of cues, including tone, pitch, facial expressions, eye contact, and body language. These improvements are facilitating the integration of AEI into professional roles that heavily rely on communication skills. Notable applications of AEI include predicting real-time anxiety in public speaking, enabling product managers to gain a deeper understanding of customer sentiments to improve product development, assisting therapists in recognizing subtle emotional cues for targeted interventions, helping educators tailor teaching methods by monitoring student engagement, enhancing language learning with instant feedback on emotional expression, and supporting medical professionals in assessing patient emotions to provide more personalized care (Nijhawan et al., 2022; Mosleh et al., 2024; Olider et al., 2024; Ojha et al., 2024; Wei & Li, 2024).

The COVID-19 pandemic has placed immense strain on healthcare systems worldwide, highlighting the transformative potential of AEI in enhancing patient care through personalized, empathetic interactions. AEI-powered virtual assistants and chatbots play a pivotal role by managing medications and offering emotional support, while its application in clinical psychology represents a significant step toward automating mental health diagnostics (Le Glaz et al., 2021). In mental health, AEI excels in automating the diagnosis of psychological disorders by leveraging multimodal data such as text, voice, and visual cues to assess the severity of conditions (Zhou et al., 2020). Specifically, AEI analyzes narrative styles, subjective speech patterns, and structured communication to infer details about an individual's education level, socioeconomic status, living conditions, and cultural background which are key elements in mental health diagnostics (Le Glaz et al., 2021). Innovations like voice-based diagnostics and facial expression analysis offer promising avenues for depression scoring and early detection of disorders such as schizophrenia (Zhou et al., 2020). Despite its potential, AEI faces challenges such as variability in emotional expressions and limited availability of high-quality data (Zhou et al., 2020). The integration of AEI into healthcare represents not just technological progress but also a critical intersection between compassionate care and advanced automation. Moving forward, the successful adoption of AEI will require a collaborative approach that combines technological innovation with human empathy to redefine patient care while ensuring equitable access to quality healthcare.

AEI is making significant progress in marketing, aiming to enhance customer experiences and optimize marketing strategies (Liu-Thompkins et al., 2022). Key applications of AEI in this field include improving sales, analyzing customer sentiments, optimizing content marketing, and deploying empathetic chatbots for customer service. By leveraging behavioral and emotional data, AEI allows brands to personalize customer interactions and deliver tailored messages that resonate more deeply with their audience (TechRadar, 2020). However, despite these advancements, significant challenges persist. One of the key issue is AEI's reliance on vast amounts of emotional data, which raises critical privacy concerns and poses regulatory challenges. Additionally, improving AEI's ability to accurately interpret emotions and replicate social presence remains a complex and ongoing task (Liu-Thompkins et al., 2022). Future developments in AEI for marketing aim to enhance personalization in human-AI interactions, create more human-like chatbots, and foster empathy in conversational agents to strengthen brand-consumer relationships (CMSWire, 2023; Liu-Thompkins et al., 2022). As AEI evolves, its integration into marketing represents a balance between technological efficiency and emotional intelligence. By combining data-driven insights with empathetic understanding, AEI has the potential to redefine customer engagement and loyalty while addressing ethical concerns such as privacy and transparency.

In content marketing, AEI utilizes multimodal methods to monitor real-time emotional responses to video content, such as advertisements and trailers (Alqurashi et al., 2023). Tools like nViso analyze viewers' emotional reactions to optimize content promotion strategies and predict the potential success of movies at the box office (Alqurashi et al., 2023). These applications enable marketers to tailor video content more effectively to audience preferences, enhancing both engagement and overall effectiveness.

AEI has become increasingly impactful in sales by enabling detailed customer sentiment analysis and predicting escalation risks. Through multimodal approaches, such as natural language processing (NLP) and voice recognition, AEI analyzes customer interactions to identify emotions and sentiments throughout the sales journey (Werner et al., 2019). Applications like BenchSci and Cyrano.AI enhance customer interactions by interpreting emotional cues, while Gong uses machine learning (ML) and NLP to refine sales pitches based on customer emails and video chat analyses (Limon & Plaster, 2022). These tools improve communication for sales professionals, boosting customer engagement and sales performance. For instance, sentiment analysis of customer support exchanges has achieved up to 73% accuracy in identifying escalation candidates using partial data analysis (Werner et al., 2019).

AEI is increasingly being integrated into the modern workplace to support employee well-being and optimize workflows (Mantello & Ho, 2023). Human resources (HR) departments are leveraging wearable technologies to monitor stress indicators, such as heart rate and electrodermal activity, providing valuable insights into employee well-being. This data enables timely managerial interventions to mitigate burnout, prevent conflicts, and address organizational "stress hot spots" effectively (Mantello & Ho, 2023). As AEI takes on more roles in the workplace, there is a growing focus on the empathetic and emotional dimensions of human work, raising important questions about the future of emotional intelligence in an AEI-enhanced environment. While AEI is expanding rapidly in the market, its application in workplace settings remains in its early stages (Gkinko & Elbanna, 2022). The adoption of AEI technologies also brings challenges related to privacy, transparency, and data governance. Future research should prioritize addressing these concerns while exploring how emotional intelligence can be seamlessly integrated into AEI applications for the workplace.

The integration of AI in education holds significant potential for transforming teaching and learning processes (Reindl, 2021). Research shows that emotional states can positively or negatively influence the learning process, impacting performance, motivation, and engagement (Tan et al., 2021; Chans & Portuguez Castro, 2021). Consequently, there has been increasing interest in studying education and learning from an emotional perspective (Schiavo et al., 2024; Yang & Zhao, 2024). Over the past decades, researchers have explored AEI in education from various angles. Applications include emotionally adaptive assessments, empathetic virtual mentors, and social-emotional learning initiatives aimed at improving self-awareness, self-management, social awareness, relationship skills, and responsible decision-making (Schiff, 2021; Yang & Zhao, 2024). Intelligent Tutoring Systems (ITS) are a prominent example, capable of monitoring student engagement and recognizing emotions such as frustration or boredom. Recent advancements aim to enhance ITS by incorporating emotional expression to foster motivation and demonstrate care for students' progress. Schiff (2021) introduces the concept of "emotional positionality" in educational agents, assigning specific emotional roles such as authoritative for teachers, motivating for mentors, and engaging for learning companions to improve the overall learning experience. As AEI's ability to predict and respond to students' emotions grows, ethical considerations become increasingly important. Concerns include the potential for AEI systems to inadvertently shame students or misinterpret their emotions. This highlights the need for critical evaluation by educational practitioners and policymakers to ensure that AEI technologies are implemented responsibly and effectively.

METHODOLOGY

Bibliometrics is a specialized subfield within library and information science that utilizes quantitative methods to analyze bibliographic data, including publication and citation metrics, through statistical techniques (Broadus, 1987; Pritchard, 1969). This approach enables the classification and comprehensive overview of bibliographic collections. Bibliometric analysis plays a pivotal role in identifying emerging trends in the performance of articles and journals, as well as in examining research stakeholders such as authors, countries, institutions, topics, collaboration patterns, and scientific developments. Additionally, it contributes to the exploration of the intellectual structure within established research domains by systematically analyzing large volumes of unstructured data through robust methodologies (Donthu et al., 2021; Merigó et al., 2018). The increasing recognition of bibliometric studies within the scientific community underscores their growing significance in academic research.

This study is a bibliometric analysis that employs a five-step literature review process, a method previously utilized by several prominent researchers, to identify and systematically examine the relevant articles (Seuring et al., 2005; Dohale et al., 2020). The steps involved in the article analysis are as follows:

Step 1: Rationale for selection of time period

The articles included in this review cover a two-decade period, from 2000 to 2025, with this time frame selected based on the significance and evolving nature of the topic under investigation. The analysis specifically commences in 2020, as a notable increase in major research studies on artificial emotional intelligence has occurred since that year. In contrast, the Scopus database revealed a relatively limited number of publications related to artificial emotional intelligence for the selected keywords between 2000 to 2019. The decision to focus on this period for bibliometric analysis was driven by the research question, the objectives of the study, and the availability and comprehensiveness of relevant data.

Step 2: Rationale for selection of database

In this review, articles on artificial emotional intelligence were sourced from the Scopus Core Collection, maintained by Elsevier. The Scopus database was chosen for the bibliometric review due to its extensive coverage of literature related to artificial emotional intelligence and the social sciences, including sources from international and non-English language publications. Additionally, Scopus offers advanced citation tracking features, which facilitate more detailed citation metrics, such as the number of citations and the h-index. The integration of Scopus with Mendeley further supports the citation tracking process in a convenient manner. Scopus encompasses approximately 36,377 titles from around 11,678 publishers, with 34,346 peer-reviewed journals across three types of sources: book series, journals, and trade journals. As a singular source for bibliometric research, Scopus has been utilized in several significant published works (Pham-Duc et al., 2022).

Step 3: Rationale for paper selection

The Scopus Core Collection database was utilized with subsequent advanced query: TITLE-ABS-KEY (“Artificial” AND “Emotional intelligence”) to retrieve all scientific documents pertinent to these topics. The data were extracted in November 2024, and the choices are restricted to journal papers that have reached the final stage of publication. A search using these keywords yielded over 656 documents published between 2000 to 2025. Following the screening process, a total of 392 documents were retained. Subsequently, the corpus was refined to include only publications that fell within the parameters of the research. The manual screening was performed by two writers who evaluated the titles, abstracts, and keywords. A total of 351 papers were selected for further investigation.

Figure 1 presents a comprehensive overview of the article selection process based on the PRISMA flowchart for systematic reviews. The PRISMA flowchart offers several key advantages, including a detailed, rigorous checklist that enhances the quality of bibliometric analysis, systematic review reporting, and meta-analyses. This structured approach aids academics and researchers in conducting more transparent and reproducible research (Page et al., 2021).

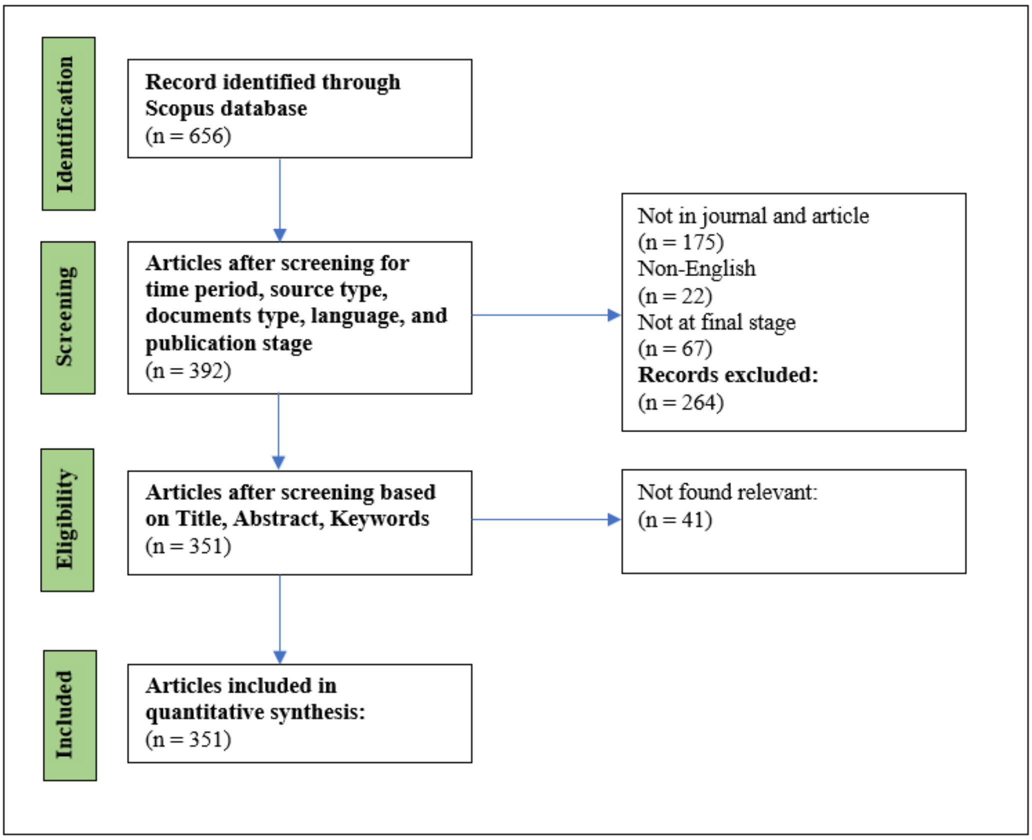

Figure 1: PRISMA flowchart for systematic review

Note: Data extracted from Scopus Database in November 2024

Source: Created by the author and adapted from Page et al. (2021)

Step 4: Review using VOS viewer and analysis

In any scientific discipline necessitating investigation, the employment of an appropriate science mapping technique is essential (Al Qudah et al., 2023). While a variety of software programs are available for this purpose, the most widely recognized include VOS viewer, Gephi, Citespace, Hist Cite, and Sci2. For the bibliometric analysis conducted in this study, VOS viewer was utilized. This software generates two-dimensional maps through mathematical techniques, establishing itself as a valuable tool in numerous bibliometric studies. VOS viewer provides insightful graphical representations of network data and effectively illustrates the structure and interconnections among various categories of data, including authors, references, keywords, journals, organizations, and countries. Furthermore, it elucidates diverse relationships such as co-authorship, co-occurrence, citation, bibliographic coupling, and co-citation (Li et al., 2021).

Using VOS viewer, a co-occurrence analysis of the authors' keywords was performed to identify the most prevalent terms and the relationships among them, with a specific focus on keywords that co-occur within the same articles. Following data cleaning, the researchers employed both Excel and VOS viewer for data analysis to examine the evolution of the literature corpus on artificial emotional intelligence during the study period from 2000 to 2025. Results from Scopus database were utilized as a data analysis tool for descriptive statistics, including information on number of documents according to the year, documents by source, type, subject area, countries, affiliations, and funding. Additionally, a co-occurrence network was constructed by extracting all keywords from the dataset using VOS viewer. This network provided insights into the relationships between terms and illuminated prevailing research interests within the field. By analyzing these co-occurrences, researchers were able to gain a more nuanced understanding of how various concepts related to artificial emotional intelligence intersect within the existing body of literature. Additionally, a comprehensive citation, co-citation analysis was conducted on the 351 articles retrieved from the Scopus database. VOS viewer Software (version 1.6.20), was utilized to facilitate the interpretation of interrelationships. Distance-based maps were constructed in VOS viewer, with the distance between two nodes representing the strength of their relationship (Van Eck & Waltman, 2022).

Step 5. Research gaps identified

A comprehensive review and analysis of the existing literature revealed several key research gaps. These gaps highlight areas where further investigation is needed to advance the field of artificial emotional intelligence (AEI). Based on these findings, the study proposes potential directions for future research, aiming to address these gaps and enhance the understanding and application of AEI in various domains.

Limitation

This study aimed to systematically review and analyze the existing literature on the integration of artificial intelligence within the domain of emotional intelligence. The literature review was based on scholarly articles retrieved exclusively from the Scopus database, a widely recognized and reputable source within the scientific community. However, it is important to acknowledge that this reliance on a single database may have limited the inclusion of relevant studies published in other databases or within the gray literature.

Furthermore, the review was confined to English-language publications, introducing a potential linguistic bias. As a result, research published in other languages was excluded, which may have restricted the geographic and cultural diversity of the findings and potentially omitted valuable perspectives.

An additional limitation concerns access bias. Although efforts were made to incorporate a broad range of academic sources, only studies that were either open access or accessible through institutional subscriptions were included. Consequently, research behind paywalls may have been inadvertently excluded, potentially affecting the comprehensiveness of the review.

Finally, the literature search covered publications from the year 2000 through early 2025. As such, the review may not fully capture the most recent advancements, methodologies, or emerging ethical considerations in the field of AEI. This temporal limitation may influence the relevance and applicability of the findings to current AEI developments. Therefore, the results of this review should be interpreted with an awareness of these methodological constraints.

RESULTS

According to the methodology described in the above section, this section presents the results of a comprehensive bibliometric analysis of scientific publications related to artificial emotional intelligence. The results are disclosed according to the unit of analysis under investigation, such as articles, authors, journals, and identification of conceptual research themes in this field. The final purpose of this bibliometric analysis is to present a comprehensive picture of past, current, and emerging trends in artificial emotional intelligence.

Descriptive Analysis

As presented in Figure 1, this study is based on 351 articles on artificial emotional intelligence related to various disciplines. This descriptive analysis provides an overview of the development and distribution of artificial emotional intelligence topic from the following perspectives: number of publications per year, documentation per year by source, most prominent authors, affiliations, and countries.

Evolution over time of the number of publications per year

Figure 2 represents the number of research publications on the topic of artificial emotional intelligence over time, showcasing how interest in this field has evolved. In 2000 to 2016, the number of publications remains consistently low, indicating minimal research activity or limited interest in artificial emotional intelligence during this period. This might reflect the nascent stage of the field or a lack of technological advancements needed for meaningful progress. On the other hand, in 2017 to 2023, a gradual and steady rise in research publications begins around 2017, likely due to advancements in artificial intelligence technologies, growing

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interest in human-machine interaction, and the incorporation of emotional intelligence into artificial intelligence systems. The accelerated growth could also correspond to the availability of improved computational tools and increased recognition of artificial emotional intelligence potential applications in fields like healthcare, education, and customer service. In 2024, the field experiences a sharp spike in publications, suggesting a pivotal year for artificial emotional intelligence. This may have been driven by major breakthroughs in the field, surge in funding or global research initiatives, and significant societal or industrial interest in embedding emotional intelligence into artificial intelligence systems. This could also mark the emergence of new conferences, journals, or collaborations focusing specifically on artificial emotional intelligence. Meanwhile, in 2025 to 2026, the abrupt decline to near-zero levels might reflect incomplete data for these years, especially if data collection for 2025 and beyond is still ongoing. Alternatively, it could signal a shift in research focus. Overall, the graph in Figure 2 demonstrates a growing interest in artificial emotional intelligence over the years, with a significant peak in 2024. This likely marks a milestone in the field, reflecting either technological breakthroughs or a surge in societal demand for artificial emotionally intelligent systems.

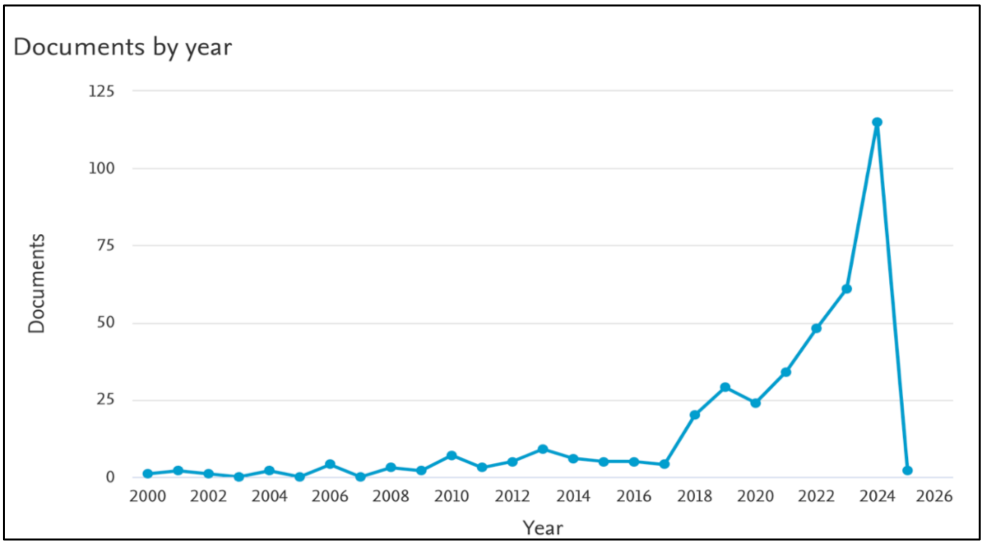

Figure 2: Evolution over time of the number of publications per year

Source: Results from Scopus database

Documents per year by source

Figure 3 represents the graph compares the number of research publications on the topic artificial emotional intelligence over time by different publication sources. *Biologically Inspired Cognitive Architectures* source shows consistent activity from 2013 to 2018 with publications fluctuating around 1 or 2 per year. After 2018, it does not contribute any new publications, indicating a decline of shift in focus. *Sustainability Switzerland* source appears to publish actively starting in 2019, peaking in 2021 with the highest number of publications (around 7). However, its contribution drops sharply in 2022, with 2 publications in subsequent years. This might reflect a temporary focus or relevance of artificial emotional intelligence. *Procedia Computer Science* contributions begin in 2018 and slightly decrease in 2020. However, in 2021 to 2022, this source maintain steady activity. This suggests a growing alignment between the field of artificial emotional intelligence and computer science applications. *IEEE Access* publications start appearing from 2021, showing a clear upward trend, with 2024 reaching its peak. This indicates a recent and increasing interest in artificial emotional intelligence by this high-impact source. Meanwhile, *ASEE Annual Conference and Exposition Conference Proceedings* shows sporadic activity with a peak in 2024. This suggests a specific event or conference focusing on artificial emotional intelligence during that year. Overall, the graph in Figure 3 highlights the diversification of sources contributing to research on artificial emotional intelligence over time. *IEEE Access* and *Procedia Computer Science* demonstrate a sustained and growing interest in artificial emotional intelligence, while *Sustainability Switzerland* and other sources reflect specific, time-limited spikes in publication activity. This suggests that artificial emotional intelligence is becoming more interdisciplinary, with increasing attention from computer science and engineering domains.

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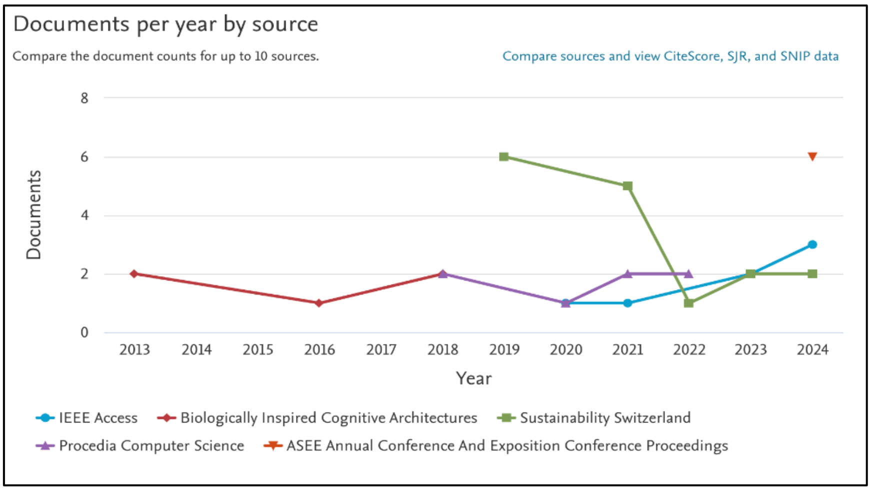

Figure 3: Documents per year by source

Source: Results from Scopus database

Documents by author

Figure 4 represents the number of documents produced by author pertaining to artificial emotional intelligence topic. The chart highlights Samsonovich, A.V. as a standout researcher with the highest impact and focus on the field. This author has contributed the most with a total of 17 publications, significantly outpacing all others. Other authors such as Andalibi, N., Chen, A.Y., Ciriello, R.F., Hannon, O., Picard, R.W., Prentice, C., Roemmich, K., Ahmadi, N., and Breazeal, C. have each contributed between 2 to 2 publications. This distribution suggests a mix of individual leadership and collective effort driving the development of artificial emotional intelligence.

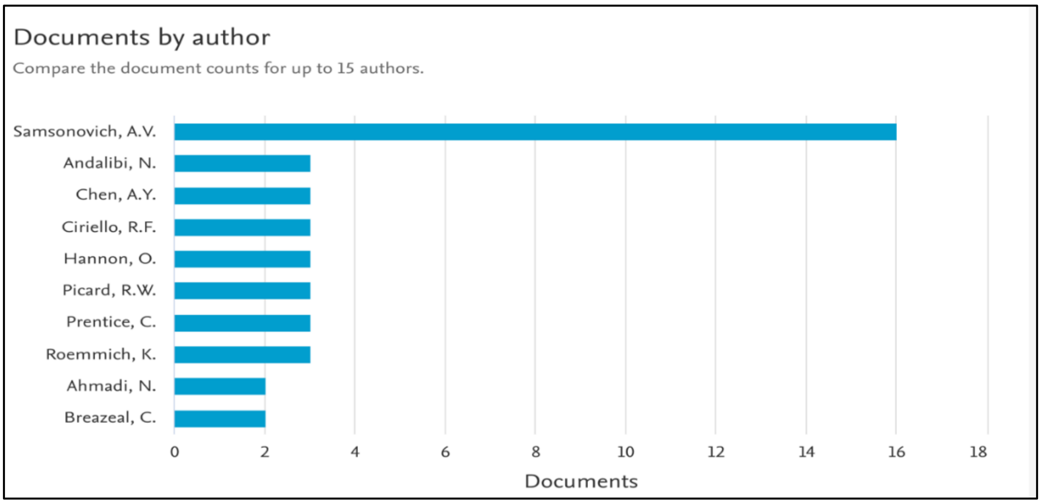

Figure 4: Documents by author

Source: Results from Scopus database

Documents by affiliation

Figure 5 shows documents by affiliation on the artificial emotional intelligence topic. The top ten contributors to the field are National Research Nuclear University, George Mason University, Tsinghua University, Pennsylvania State University, Universiti Kebangsaan Malaysia, MIT Media lab, Universiti Teknologi MARA, Sharda University, University of Johannesburg, and Universitia degli Studi di Salerno. Publications are created across the continents of Asia, North America, Europe, and Africa. However, most of the research in North America and Asia is done. The most prominent research by affiliation is done in National Research Nuclear University with 12 documents.

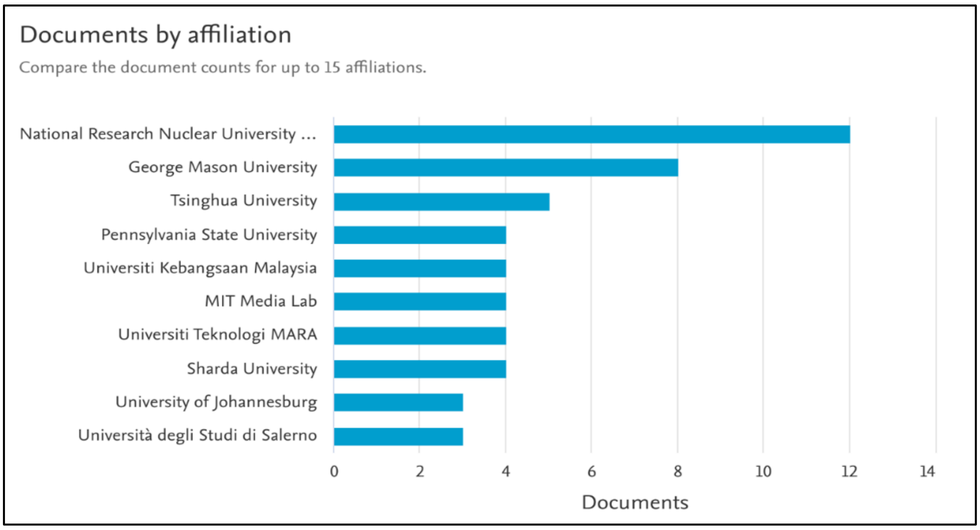

Figure 5: Documents by affiliation

Source: Results from Scopus database

Documents by country or territory

Figure 6 represents the number of research documents by country or territory pertaining to artificial emotional intelligence topic. United States is the leading contributor in publishing distribution through the country of origin, with the India in the second rank and followed by China. The plausible reasons about the United States being leading contributor to research documents on artificial emotional intelligence can be explained due to strong research ecosystem. The U.S. has a robust ecosystem of research universities (e.g., MIT, Stanford, UC Berkeley) and research-focused organizations. Funding from entities like National Science Foundation (NSF) support cutting-edge research in artificial intelligence. On top of that high visibility in top-tier journals and conferences ensures U.S. researchers are often at the forefront.

Meanwhile, based on Figure 6, United Kingdom is in fourth place, followed by Canada, Germany, Malaysia, Russian Federation, Australia, and Japan.

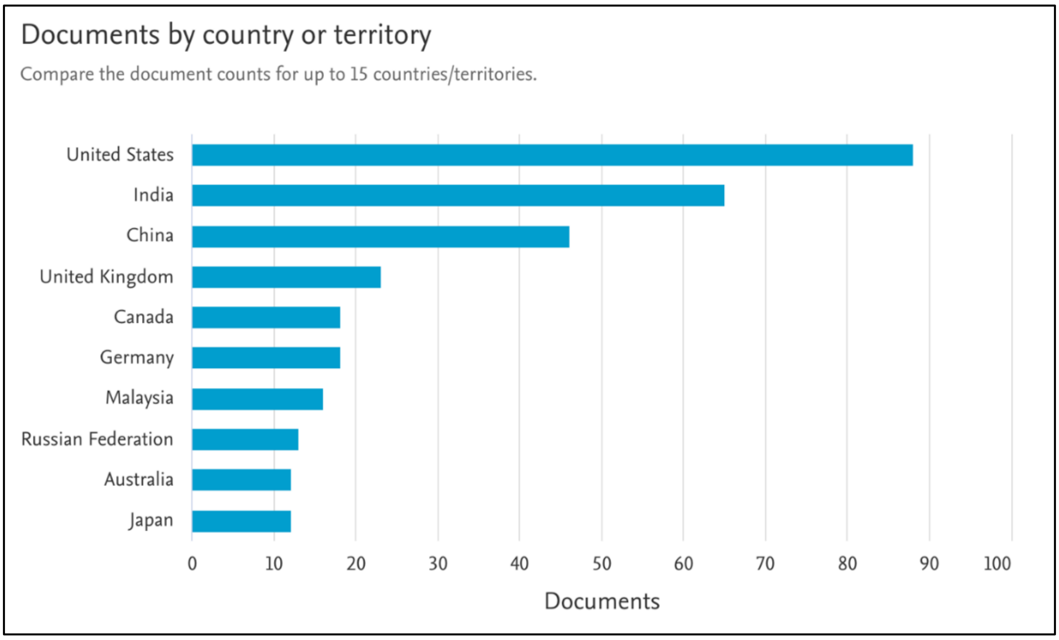

Figure 6: Documents by country or territory

Source: Results from Scopus database

Documents by funding sponsor

Figure 7 represents the number of research documents by funding sponsor on the topic related to artificial emotional intelligence. It can be seen that the prominence funding sponsor are lead by National Natural Science Foundation (NNSF) in China and National Science Foundation (NSF) in United States. This is consistent with the findings that United States and China produced corpus of research documents related to artificial emotional intelligence. The NNSF is one of the largest funding bodies in China, providing substantial financial support to a wide range of scientific disciplines, including AI and emotional intelligence. The NSF supports research across all fields of science and engineering, with a specific focus on emerging technologies like AI and its subsets, including emotional AI.

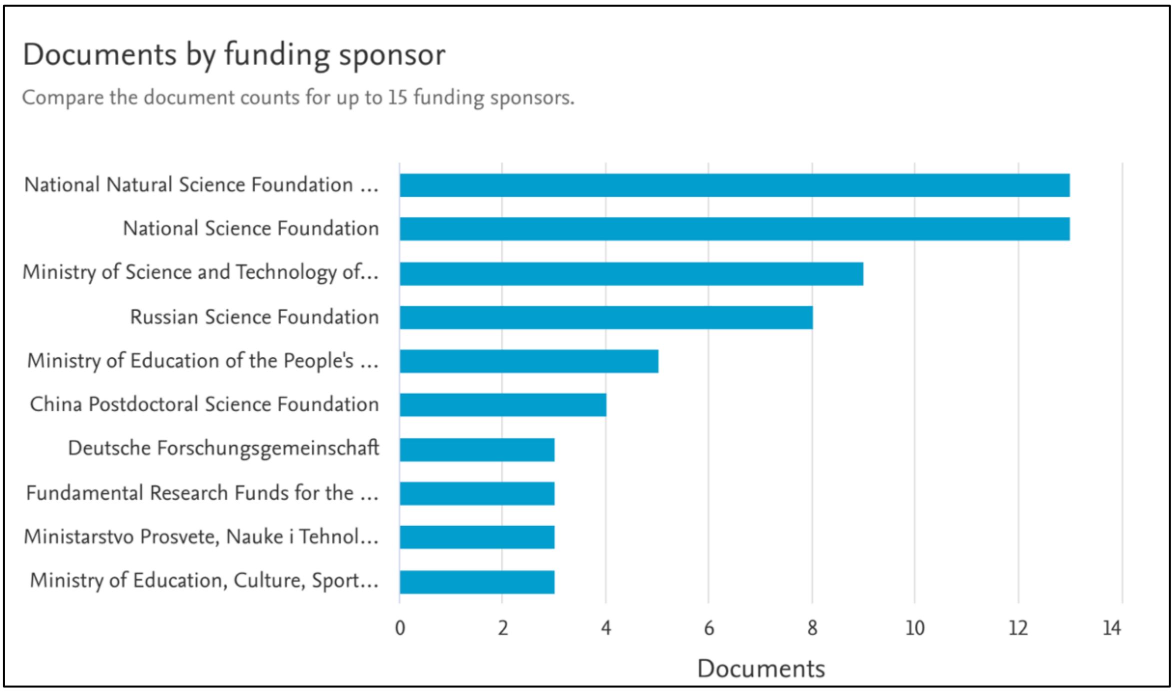

Figure 7: Documents by funding sponsor

Source: Results from Scopus database

Science Mapping Analysis

The main purpose of the science mapping analysis is to summarise the bibliometric structure and intellectual structure of the selected research field (Donthu et al., 2021; Caputo et al., 2021), by using certain techniques for science mapping (such as co-citation analysis, co-occurrence analysis, bibliographic coupling, co-authorship analysis) combined with enrichment bibliometric techniques (such as networks and clustering visualisation).

Co-citation analysis

As noted above, co-citation analysis includes the evaluation of the references cited by the scientific publications included in the selected dataset and the analysis of the relationships among cited publications to better understand the development of foundational themes in a certain research field. In other words, as highlighted by Ferreira (2018), co-citation analysis allows for the identification of publications that are co-cited by several other articles, which means that these cited publications are somehow meaningfully related. For our sample of 351 articles, a minimum threshold of 8 citations of a cited reference was considered, which contained 14991 cited references that met the threshold. To foster an understanding of the co-citation analysis of articles, Figure 8 illustrates the network diagram, allowing visualisation of the co-citation network of researchers in the field of artificial emotional intelligence.

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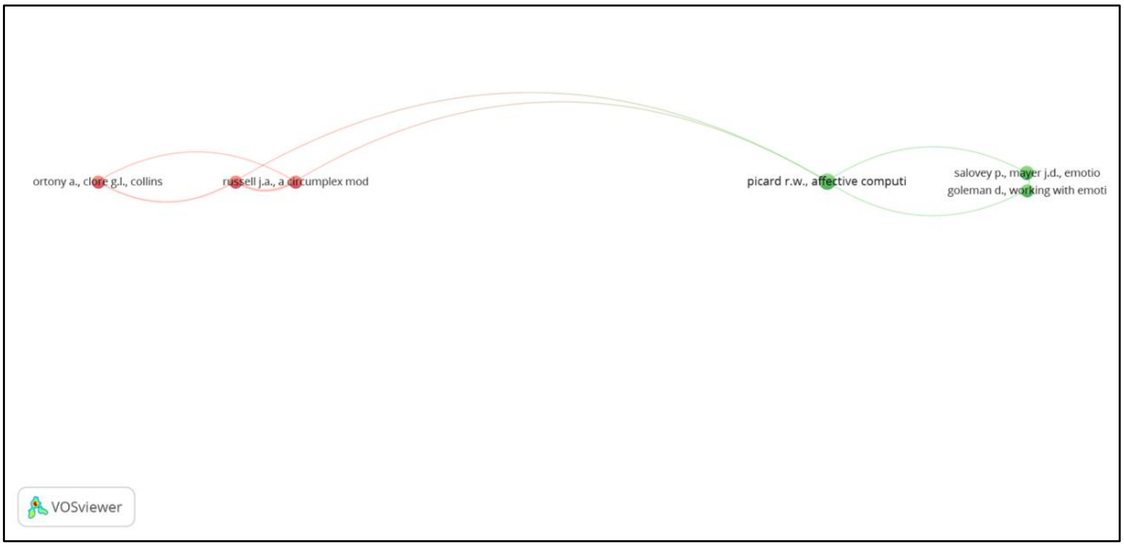

Figure 8: Co-citation based on authors

Source: Created by the author based on the VOSviewer analysis

According to the Figure 8, there are two major clusters of cited references. Red cluster has 3 cited references, and green cluster has 3 cited references. The cited references included in the red cluster focused mainly on cognitive structure of emotions, model of emotion, and mental state. Meanwhile, green cluster focused mainly on emotional intelligence, artificial emotional intelligence, and cognitive emotional intelligence.

Co-authorship analysis

Co-authorship analysis examines the intellectual collaboration between researchers and research institutions based on the number of publications jointly authored. The type of analysis is widely used to understand and assess patterns of scientific collaboration in certain research fields. For our sample of 351 articles with a minimum threshold of one publication per author was considered; the resulting set contained 745 authors who met the threshold. To provide a better understanding of the co-authorship analysis, Table 1 presents the top ten authors classified based on the total link strength of the co-authorship. It can be seen that the author Samsonovich, Alexei was the most collaborative author from the selected sample of 351 articles. To foster better understanding, Figure 9 represents the network diagram, allowing visualisation of the co-authorship network of researchers in the field of artificial emotional intelligence. Based on the diagram, there are five different clusters of co-authorship.

Table 1: Top 10 most collaborative authors in the selected sample in the field of artificial emotional intelligence

No.	Author	Documents	Citations	Total link strength
1.	Samsonovich, Alexei	11	251	15
2.	Cao, Zehong	1	26	10
3.	Chen, Badong	1	26	10
4.	Chen, Huafu	1	26	10
5.	Li, Cunbo	1	26	10
6.	Li, Fali	1	26	10

7.	Li, Ning	1	26	10
8.	Li, Peiyang	1	26	10
9.	Si, Yajing	1	26	10
10.	Xu, Peng	1	26	10

Source: created by the author based on the VOSviewer analysis.

Note: In this case, the total strength represents the total strength of the co-authorship links between a given author and other authors.

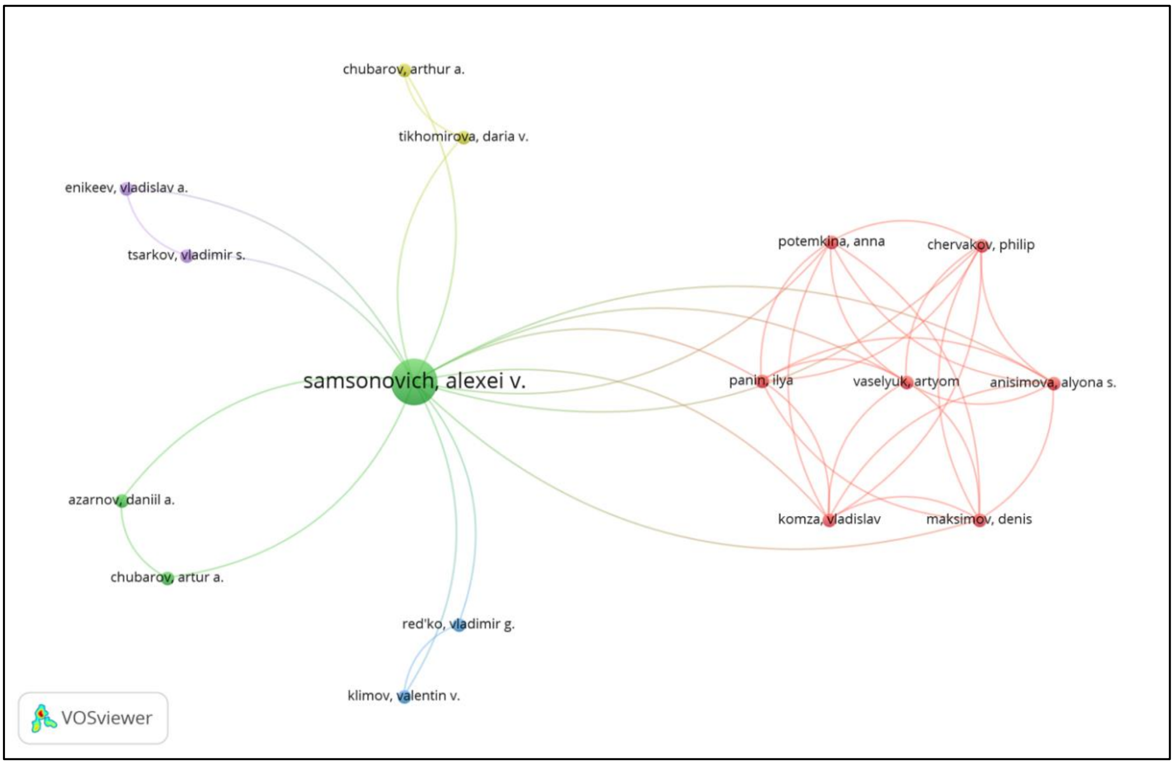

Figure 9: Co-authorship analysis

Source: Created by the author based on the VOS viewer analysis

Co-occurrence analysis of keywords

Keyword network analysis plays a crucial role in bibliometric studies by revealing the level of international interest and identifying research hotspots in disciplinary areas, which can promote scientific research support and recognition. In this section, we used the word co-occurrence network map to examine artificial emotional intelligence. With multiple occurrences of 5 and a threshold of 2888 keywords related to artificial emotional intelligence were discovered across 351 studies in the area. The domain's resulting word co-occurrence network map was displayed using a VOSviewer. Six clusters using VOSviewer have been developed to their full potential. When viewing the map, identical colored nodes may be seen. Cluster together to form clusters; the clusters' proximity to one another indicates how strong the clustering is. Consider that the thickness of the line represents the level of co-occurrence. Figure 10 comprehend the co-occurrence of the keywords.

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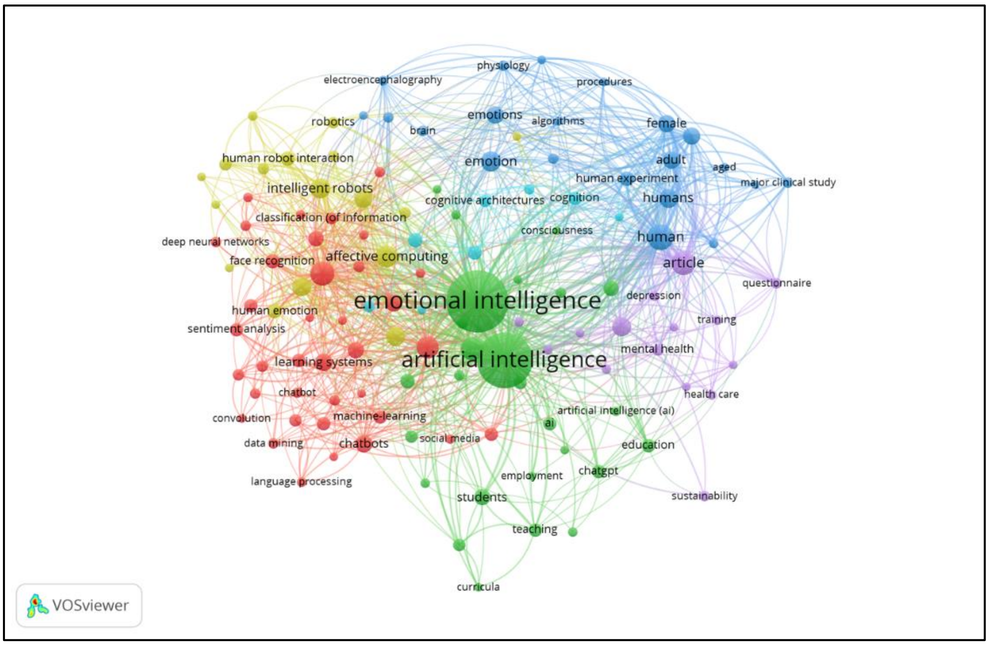

Figure 10: Co-occurrence analysis of keywords

Source: Created by the author based on the VOS viewer analysis

The six clusters were identified as follow; Cluster 1: emotion recognition (37 occurrences), Cluster 2: emotional intelligence and artificial intelligence (26 occurrences), Cluster 3: human (21 occurrences), Cluster 4: intelligent robots (17 occurrences), Cluster 5: psychology (15 occurrences), and Cluster 6: social interactions (8 occurrences). To foster an understanding of the co-occurrence of keywords, Figure 11 shows the cluster density visualization of high-frequency keywords which is enriched visualisation because the density of keywords is displayed separately for each cluster of keywords. Another useful diagram is the overlay visualisation, which allows the identification of the temporal distribution of keywords in each cluster as depicted in Figure 12. In overlay visualisation, keywords are coloured according to a score that is computed based on the average year of occurrence of a keyword. Thus, colours vary from blue (the oldest year) to green to yellow (most recent years). Analysing overlay visualisation, one can note that the field of studies on artificial emotional intelligence has evolved from a previous focus on topics such as affective computing, human computer interaction, and emotion recognition (oldest years) to more integrated and challenging concepts such as artificial emotional intelligence in education, training, chatgpt, chatbots (most recent years) and most recent technological developments which will bring more challenges to this research field.

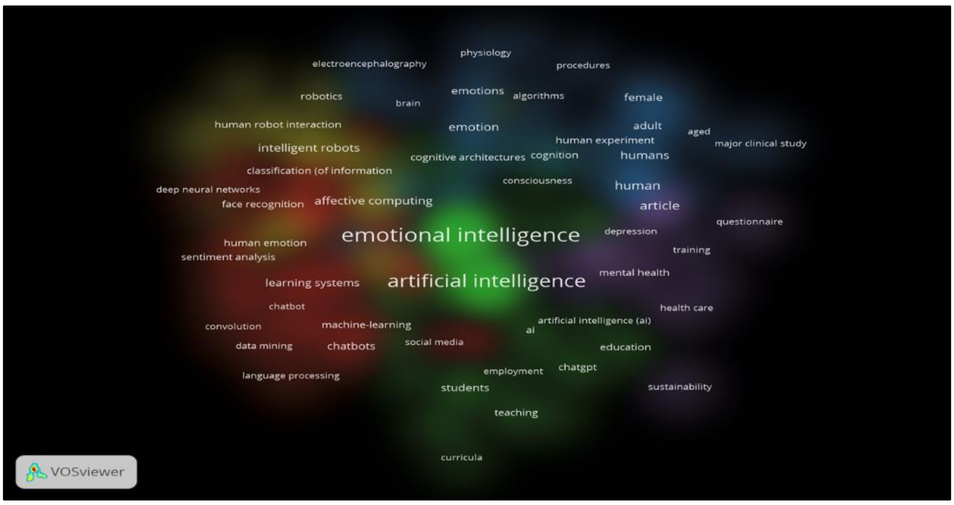

Figure 11: The co-occurrence analysis of keywords density diagram using cluster density

Source: Created by the author based on the VOS viewer analysis

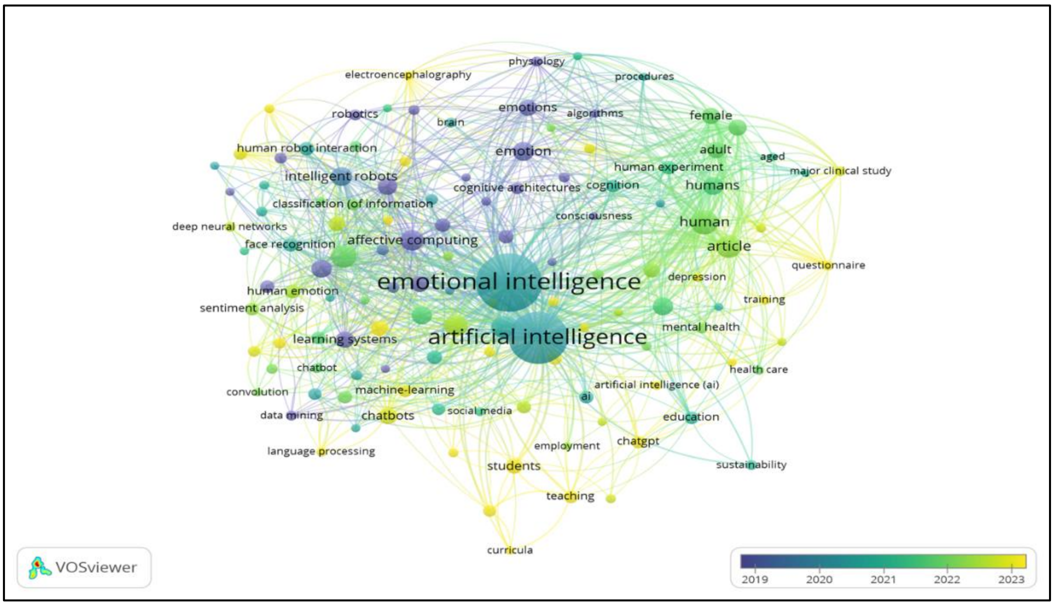

Figure 12: The co-occurrence analysis of keywords overlay diagram

Source: Created by the author based on the VOSviewer analysis

CONCLUSION

As AEI continues to mature, researchers are focusing on enhancing its capabilities through interdisciplinary approaches that combine insights from psychology, philosophy, and technology. This includes addressing ethical implications and ensuring that AI systems are designed with human-centric values in mind. The potential for AEI to facilitate more compassionate interactions between humans and machines presents exciting opportunities for future research and application.

The bibliometric analysis of AEI using VOSviewer highlights the dynamic growth and interdisciplinary nature of this emerging field. By examining trends, influential publications, and collaborative networks, the study underscores the increasing relevance of AEI across diverse domains such as education, healthcare, marketing, and workplace. From the findings, it can be concluded that there is a significant increase in publication on the topic related to AEI during 2023 to 2024. Most of the research producing institutions, journals, authors, articles, and collaboration with the highest citation were from the United States, followed by India and China. In the list of top-ranked journals, *IEEE Access* publications start appearing from 2021, showing a clear upward trend, with 2024 reaching its peak. This indicates a recent and increasing interest in AEI by this high-impact source. The top author in AEI, based on research publication showed that Samsonovich, A.V. as a standout researcher with the highest impact and focus on the field. This author has contributed the most with a total of 17 publications, significantly outpacing all others. Regarding institutions and universities, the most prominent research by affiliation is done in National Research Nuclear University with 12 documents.

The findings of this study highlight significant advancements in emotion recognition models, the integration of multimodal and the growing applications of AEI in enhancing human-computer interactions. The co-occurrence analysis of keywords highlighted the prominence use of AEI in the area of ChatGPT, chatbots, human-robot interactions, machine learning, and curricula for education. Despite these advancements, challenges such as cultural variability, data privacy concerns and ethical implications continue to present obstacles. These challenges require a critical evaluation of current methodologies and responsible implementation practices.

Future research should prioritise on addressing these challenges through international collaboration, refining cross-cultural emotion recognition models, and ensuring transparency and ethical integrity in data governance. Moreover, integrating emotional intelligence into AI systems offers transformative opportunities to develop more empathetic and responsive technologies that align with human values. This bibliometric analysis not only maps the current landscape of AEI research but also lays a foundational path for advancing the field, ultimately redefining human-AI interactions across diverse industries.

In conclusion, AEI represents a transformative frontier in AI research, bridging the gaps between human emotional intelligence and machine learning capabilities. As this field continues to evolve, it holds tremendous potential to improve applications in sectors such as education, healthcare, marketing and workplace optimization. However, it also raises important ethical considerations that must be thoughtfully addressed to ensure responsible and beneficial AI development.

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