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Emotional and Social Competencies of Artificial Intelligence: Measurement, Results, and Insights

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Abstract: *In recent years, interest in developing emotional and social skills in artificial intelligence has grown significantly. The present study aims to explore the options for measuring the emotional and social aspects of artificial intelligence, as well as to analyse the generated results and the formulated conclusions and generalisations. An analysis of existing and widely used chatbots with artificial intelligence was conducted, and the emotional and social intelligence of AI was assessed using a non-standardised test questionnaire. The findings provide essential conclusions, not about the possibilities for measuring the intrapersonal and social skills of AI, but rather about the current state of its development and its ability to generate emotional and social insights. The authors also establish a correlation between the affective and interpersonal intelligence demonstrated by AI and collective (global) emotional intelligence as a concept. In conclusion, the article discusses the potential applications of these results in various fields, including enhancing communication capabilities between humans and machines, among humans themselves, and even between machines. This study provides essential data and directions for future research and applications in the field of human emotional and social intelligence, as well as AI, acknowledging the use of free chatbot versions and a non-standardised questionnaire. In this sense, the insights obtained enrich both the theoretical and applied knowledge in the fields of information, communication technologies, and social sciences, including management and human resources.*

Keywords: *emotional and social intelligence; artificial intelligence; collective intelligence; emotional artificial intelligence.*

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1. Introduction

Emotional and social intelligence (ESI) generally refers to an individual's awareness of their current feelings. Professionally, it encompasses essential skills like effective communication, teamwork, and impulse control. More narrowly, ESI is the science of emotional regulation and interpersonal relations, involving behavioural adaptation based on awareness of one's own and others' emotions. Thus, ESI integrates thoughts, actions, and feelings towards oneself and others through components such as self-awareness, self-management, social awareness, relationship management, and social skills (Boyatzis et al., 2019).

Artificial intelligence (AI) involves machines that are capable of learning, adapting, and making informed problem-solving decisions, rendering AI applications increasingly indispensable across diverse fields. AI has quickly become commonplace, now routinely writing, reading, analysing, thinking, human-like decisions, and recognising diverse emotions (e.g., joy, anger). These applications leverage human emotions and knowledge to enhance convenience, productivity, and well-being (Somers, 2019; Kordon, 2023).

Despite optimism, fears persist that AI may replicate or surpass human capacities perfectly. The nature and future of AI evoke both hopes for a better future and fears of catastrophic outcomes, such as Armageddon or technological enslavement (Shnurenko, 2022), with some viewing intelligent machines as an existential risk. However, Hawkins (2021) suggests that machine intelligence is not inherently malicious; rather, the danger lies in its human application, similar to that of other powerful technologies. AI is undergoing a renaissance, continually revealing new applications and improved results, particularly in the dominant field of artificial neural networks. Yet, these current networks significantly differ from human brain neurons. Hawkins (2021) argues AI's future depends on new principles that more closely imitate the human brain.

Although the human brain has been compared to a computer, information processing is inextricably linked to emotions. They are just as important as reason in guiding thoughts and decisions, although they function differently. Intelligence is associated with the ability to think, understand, and form a mental picture of reality, with rational thinking allowing for logical conclusions. At the same time, emotions have a profound influence, shaping the meaning of goals and the importance of information, and creating a necessary constructive framework for evaluation (Mlodinow, 2022; Shkëmbi & Treska, 2024).

Humans are social beings who need interaction to build complex social structures; the formation of groups and interpersonal relationships is fundamental to human nature, development, adaptation, and influences their evaluations. Intelligence is built on broad, lifelong experiential learning, and knowledge of the world. Through education and experience, the brain gradually forms a complex, interconnected model of the environment, from basic concepts to abstract ideas such as compassion. This organised pattern is the basis of intelligence (Young, 2008; Hawkins, 2021).

Rooted in both knowledge and experience, emotions invariably alter these patterns, often in subtle but significant ways. They also modulate perception of their current situation and shape their expectations for the future (Mlodinow, 2022). Human emotions are emergent properties of neural processes, and our understanding of the world is built upon models that also contribute to forming emotions. And if, in the future, we expect more advanced AI that imitates the human brain, can we expect the AI to develop emotions, emotional capacity, even emotional and social intelligence analogous to humans?

This paper aims to explore the feasibility of integrating emerging and developing ESI into current and future AI applications. The study focuses on AI applications that have access to massive data, reflecting the knowledge and experience of the global population. The central thesis is that this access will allow AI to demonstrate advanced ESI-like functions.It is further assumed that the two selected chatbots, working with similar data and models, will show the comparable ESI-like outputs. These assumptions are the basis of the study's hypotheses.

The formulated thesis and hypotheses are essential from the perspective of growing concerns among people regarding AI applications and their vast and expanding potential. It is crucial not to

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attribute human qualities (such as emotionality) to AI that it cannot possibly possess. This requires AI to be conceptualised as distinct and to analyse the potential demonstration of human qualities on its part. More productive and open-minded human-machine collaboration may lie in this analysis. The study is structured as follows: 1) Basic theoretical constructs in the field of ESI and AI are analysed; 2) The research methodology, main theses, and hypotheses are formulated; 3) Conducting research, synthesising, and analysing the results; 4) Formulating theoretical generalisations, limitations of the research, guidelines for the applicability of the generated new knowledge, and suggestions for future research.

2. Literature review

2.1. The Construct of Emotional and Social Intelligence

ESI is viewed as a multifactorial set of interrelated emotional, personal, and social abilities that influence a person's overall ability to actively and effectively cope with everyday demands. Bar-On (2000) presents data on the development and psychometric properties of the Emotional Intelligence Quotient, including internal consistency, reliability, stability, factor structure, and validity. The factor structure of the construct consists of the following ten components: self-esteem, emotional self-awareness, confidence, empathy, interpersonal relationships, stress tolerance, impulse control, reality testing, flexibility, and problem-solving. In addition to these key components, five facilitators of emotionally and socially intelligent behaviour have been described: optimism, self-actualisation, happiness, independence, and social responsibility.

The concept of emotional intelligence (EI) can be visually represented by a model of three components: awareness, adjustment, and adaptability. Awareness is the understanding of what is happening inside a person. Adjustment involves observing others and interpreting these observations to foster cognitive and emotional empathy. Adaptability uses awareness and adjustment to choose the most constructive response to the given conditions.Some models equate awareness and adjustment together conceptualised as EI, and adjustment and adaptability constitute social intelligence (SI). Together, they form the complete construct of ESI (Bar-On, 2000).

Mayer and Salovey, cited by Shkëmbi & Treska (2024), define EI as a set of cognitive skills that include *perceiving, facilitating, understanding*, and *managing emotions.* Effective emotion management necessarily requires recognising and regulating emotions in oneself and others, as well as applying cognitive skills. For this reason, the two authors incorporate the concept of SI into their definition of EI (Rehman, Dhiman, & Cheema, 2024). In their study, D'Amico & Geraci (2023) conceptualised EI as individuals' perceptions of their affective world. According to Daniel Goleman, EI is a potential factor that determines the acquisition of practical skills in five aspects: self-awareness, self-motivation or optimism, self-control, empathy, and relationships with others. Thus, EI quite naturally fits into the construct of SI since human social relationships drive people's emotions (Shkëmbi & Treska, 2024; Goleman, 1995; Goleman, 2006).

In an effort to establish that the two categories are an important psychological dimension that influences various aspects of daily life and health, scientists have arrived at the general construct of ESI. As a result, both the models and definitions, as well as the assessment instruments, are highly heterogeneous from each other, and this causes a large and still active debate in the scientific literature (D'Amico & Geraci, 2023). Depending on the chosen model for assessing ESI, self-assessment tests, situational tests, and tests based on the performance of a given case are applied.

Although EI and SI are related, they are not precisely the same thing. Emotional vs. social intelligence can be viewed as the difference between the way a person relates to oneself versus the way he relates to others. When comparing EI with SI, it becomes clear that the former involves self-awareness and self-regulation. SI, in turn, is less concerned with one's emotions or reactions and more focused on sensitivity to the emotions, moods, and motivations of others, and the ability to interact with others as part of a group (Boyatzis et al., 2019). This theoretical connection is reflected in the broader adoption of the concept of ESI.

2.2. The Artificial Intelligence Paradigm

Artificial intelligence refers to the imitation of human intelligence (HI) by machines. This field is constantly evolving and includes various technologies, including machine learning (ML) and deep learning (DL). ML enables software to predict outcomes with greater accuracy without being explicitly programmed to do so. Its algorithms are statistical and based on extracting patterns from large data sets. DL, a subset of ML, is inspired by the architecture of the human brain and uses artificial neural networks. It is key for recent advances in AI, such as self-driving cars, chatbots, ChatGPT, and Gemini. In corporate information technology, AI, ML, and DL are often used as generic terms, although there are significant differences between them. Companies sometimes use them interchangeably, especially in their marketing messages. Usually, what the public and many experts refer to as AI is simply a component of technology, such as ML (Solaiman & Salaheen, 2019; Berditchevskaia & Baeck, 2020).

This shows that ML has become the most popular and recognisable aspect of AI. In this, a machine or program follows statistical models for pattern recognition to improve its ability to make decisions. As data accumulates, the statistical power of the datasets increases, leading to more accurate pattern recognition. Through the use of statistical models (e.g., nonlinear regression), a number of outcomes can also be better predicted (Solaiman & Salaheen, 2019). In reality, end users routinely interact with AI through smartphones, virtual assistants like Alexa, and autopilots in cars ,all of these devices transmit data to the cloud and receive commands from there (Shnurenko, 2022).

AI can also be defined according to its use. One type of AI is designed to imitate HI and automate human tasks in performing specific functions. This type, known as automation-focused AI, aims to replace HI. The other kind of AI, called augmented AI, aims to enhance human abilities by compensating for its shortcomings. Augmented AI uses various techniques, such as ML, decision trees, and evolutionary algorithms, to augment HI. This allows for the discovery of new knowledge by analysing patterns, functions, and relationships in data. The ability to train AI models, as mentioned several times, is one of the strengths of AI. There are three main types of AI: supervised, unsupervised, and reinforcement. Two new types have recently been introduced: semi-supervised and self-supervised. The latter are less well-known and are based on a combination of supervised and unsupervised methods (Kordon, 2023). Another feature of AI, built into its programming, is the focus on a set of functional capabilities (Solaiman & Salaheen, 2019):

- *Learning*: Focuses on acquiring data and creating rules to turn it into useful information. The rules, called algorithms, provide computing devices with step-by-step instructions on how to perform a specific task.
- *Reasoning*: focuses on choosing the right algorithm to achieve a desired result.
- *Self-correction*: This is designed to continuously fine-tune algorithms and ensure that they provide the most accurate results possible.
- *Creativity*: uses neural networks, rule-based systems, statistical methods, and other AI techniques to generate new images, new text, music, and ideas.

In addition, AI uses five types of knowledge to interact with the world, but only two of them are common to all AI systems. Each of these types of knowledge is essential for AI to interact effectively with the world. *Declarative knowledge* helps AI understand facts about the world. This is the simplest type of knowledge and describes statements as facts, for example, “cats are mammals”. *Procedural knowledg*e instructs AI on how to solve and perform specific tasks. *Meta knowledge* helps AI learn and improve its performance. *Heuristic knowledge* helps AI solve problems in uncertain situations. *Structural knowledg*e helps AI organise and use its knowledge more effectively. In some AIs, meta, heuristic, and structural knowledge provide additional information to help them solve more complex problems. It is important to note that these are just five of the many different types of knowledge that AI can use. As AI technologies advance, new types of knowledge are likely to emerge, and existing categories may be revised (Kordon, 2023).

2.3. Commonalities and Key Distinctions Between Artificial and Natural Intelligence

The terms *intelligence, wisdom, imagination, inspiration*, and *creativity* are commonly used to describe HI. The variety of meanings they cover is an indication of the many discussions that have attempted to determine the essence of the concept of intelligence. Although hundreds of definitions have been created, for most of history, intelligence has been understood as a biopsychosocial capacity to acquire and use knowledge and skills. Today, AI and machines capable of performing tasks traditionally associated with humans have caused changes in society.Since the second half of the 20th century, and at a significantly accelerated pace in the last two decades, machines have demonstrated the ability to learn and apply what they have learned in ways that, until recently, were exclusive to humans. However, human and artificial intelligence are significantly different – they are not synonymous or interchangeable. Even considering the still ongoing debate about what defines HI and AI, the differences between the two are obvious (Monteith et al., 2024).

Modern AI differs significantly from HI in many ways (Figure 1). For example, humans constantly learn and evolve their model of the world, while DL networks must be fully trained before they can be used, and cannot learn new things on the fly. Furthermore, the main difference is that AI systems are specialised and can perform only one task, while humans are multitaskers (Hawkins, 2021; Monteith et al., 2024).

The long-term goal of AI research is to create machines with human-like intelligence – machines that can quickly learn new tasks, find analogies between different tasks, and solve problems flexibly. This goal is called general-purpose AI, and it is different from today's AI. Almost all of the investment so far has been directed towards improving DL technologies (Hawkins, 2021). But will these investments lead to human-level machine intelligence, including EI, or are DL technologies inherently limited? At the same time, humans have always been better than machines at understanding emotions. But will that continue? While some doubt that machines will ever master emotions, those working in the field of artificial emotional intelligence (AEI), also known as emotional AI or affective computing, claim that they are on track to achieve it, and by the end of 2025, the global market for affective computing will reach $174 billion (Marr, 2021).

Machine (Artificial) intelligence	Vs	Human intelligence (HI)
Scale & speed	**Process**	Curiosity & intent
Consistent (inflexible) performance	**Performance**	Flexible (inconsistent) performance
Can interpret high-dimensional data	**Interpreting**	Contextual awareness & reasoning
Primary unable to learn in a multimodal way	**Information**	Multisensory input and output
Can learn from (many) examples	**Learning**	Can learn from (few) examples
Not vulnerable to social bias	**Decision-making**	Moral & ethical judgement
Based on rules, algorithms, and data, but lacks intuition and the ability to make ethical judgments.		Can make complex decisions based on intuition, experience, reasoning, and ethical considerations.
Recitation	**Problem-solving**	Imagination
Not capable of working with human emotions or problems needing emotional understanding	**Sensitivity**	Includes the aspect of emotional intelligence.
Not programmed to develop nuanced social understanding. Only some AI programs like chatbots have exetnsive codes and training data about patterns of human interaction, enabling them to communicate in ways similar to human interactions.		Humans can effectively understand, regulate and communicate their and others' emotions to each other.
Social problem-solving can be quite limited and stunted in AI systems apart from the data and codes that they have been fed with.	**Social problem-solving & decision-making**	HI is in-built with abilities for complex social communication and social problem-solving. As a result, humans have better and much more refined social decision-making abilities.
Can generate new solutions based on existing patterns and data, but lacks true creativity and originality.	**Creativity**	Can create new ideas, art, music, and literature through imagination and innovation.

Figure 1. Key aspects and differences between machine intelligence and human intelligence. Source: authors' development

2.4. Emotionally Intelligent Artificial Intelligence

Understanding emotional signals is natural for humans. In artificial agents, however, a lack of EI can lead to misinterpretations of their behaviour, which can be unexpected and confusing for humans. This can disrupt human expectations and even cause emotional harm. There is a need to investigate how much emotional intelligence artificial agents need for successful interactions. Fan et al. (2017) conducted a study aimed at determining whether people perceive robots as more or less emotionally intelligent when they exhibit human-like behaviour. The results show that respondents successfully discriminated between high and low EI, regardless of whether the agent was a robot or a human. The latter was not a determinant of human perception.

Artificial EI is the process of teaching computers to understand and respond to human emotions. By analysing a variety of data, including facial expressions, gestures, and tone of voice, computers can determine a person's emotional state. This field of research, called affective computing, dates back to 1995. As this technology develops, interactions between humans and machines are expected to become more natural and human-like (Somers, 2019; Marr, 2021). AI can analyse data to detect subtle emotional nuances that some people express, which others might overlook. Through a combination of computer vision, sensors and cameras,large-scale real-world datasets, speech science, and DL algorithms, AI systems collect data and then process and compare it with other data points that identify key emotions, such as fear and joy. Once the appropriate emotion is determined, the machine interprets the emotion and what it might mean in each case. As the database of emotions grows, algorithms increasingly improve in identifying nuances of human communication (Marr, 2021).

Although AI can simulate and analyse human emotions, it does not have the same biological basis as humans. AI can recognise emotions by analysing facial, voice, and text data, but it is not actually capable of experiencing these emotions as a human would. Essentially, AI's apparent emotionality arises from the detailed analysis of unfiltered human facial expressions using optical sensors or webcams. This usually happens in real-time, as computer algorithms reveal key points in the human face. Meanwhile, DL algorithms analyse the pixels in these fields to classify facial expressions. Finally, facial expressions are combined with specific emotions. AI is also capable of analysing the way a person speaks by observing the tone and pitch to investigate emotions (Kambur, 2021).

The common characteristic is that we are referring to trained AEI, which, through observation and analysis, can recognise and imitate human emotions. But if these variables – face, voice, or expressed emotions – are absent by default, what kind of emotional simulation would AI then demonstrate? Can we speak of an "innate" one, i.e. integrated into it, or one developed based on its experience with human EI? It is believed that human EI develops on experience and is often compared and even likened to human wisdom. Does this rule also apply to AI?

At the time of the current study, there is no specific data on whether and to what extent AI is emotionally intelligent. However, there is no lack of user data on how responsive and empathetic AI chatbots are. The breakthrough in affective computing has enabled an almost imperceptible transition from mechanical to empathetic chatbots, which are able not only to detect, decode, and imitate the thoughts and feelings of customers, but also to react appropriately. It is assumed that artificial empathy is able to bridge the gap in communication between humans and artificial intelligence (Juquelier, Poncin, & Hazée, 2025).

The experimental study aims to identify the presence of empathy in AI and the rest of the EI competencies – self-awareness, self-regulation, optimism, motivation, and social relationships. This configuration of elements includes SI in the context of empathy, social relationships, and most fully corresponds to the ESI construct. In accordance with the set goal, the conceptual framework of the study was built, and the corresponding hypotheses were formulated.

3. Methodology

The research methodology includes analysis and experimentation. The individual activities are divided into the following stages:

1) *Choosing a questionnaire for measuring ESI:*

- For the study, professional tests were used to measure emotional intelligence, which is not widely available for free reading in the online space. It is unlikely that the AI bots studied have built their models regarding what is right or wrong in the context of emotionally-socially intelligent behaviour. Such alignment is possible only with regard to the questions in the specific test set, but not for the ESI as a whole;
- Thirty-six questions, divided into six groups, measure the degree of manifestation of individual competencies, part of the general construct of ESI: self-awareness, self-control, motivation, optimism, self-motivation, empathy, and social skills. To varying degrees, these competencies are fundamental elements of both the independent construct of EI, on the one hand, and the independent construct of SI, on the other, which together form the general ESI. According to the answers, the ESI of the respondent is calculated on a predetermined rating scale of high, medium, and low;
- The authors of the current experiment chose not to publish the specific set of questions they used to measure the ESI. However, for the sake of transparency, they share that the sample of questions is a synthesis of the questionnaires of Wood & Tolley (2002), and their rating scale was also applied. In addition, the questions used in the current experiment retain the essence of the original test set, but the questions and answers are rearranged;
- For reproducibility of the present study, the complete set of questions can be made available to other scholars upon request by the corresponding author.

2) *Selection of AI chatbots on which to conduct the experiment:*

At the time of the experiment, the two most developed and most widespread AI chatbots were ChatGPT and Gemini. In the debate over which of the two is better designed, there is still no clear winner (Papers with code, 2023). For the study, the authors chose to evaluate both chatbots, which will allow for more in-depth comparative analysis and more complete conclusions between the final results of the ESI test and the parameters of the specific AI chatbot.

3) *The experiment plan:*

- New user (free) profiles were created on the ChatGPT and Gemini platforms, thus aiming to minimise the influence of previous user prompts in the AI bot's responses;
- Immediately before the start, a video recording of the human-machine "conversation" was activated. The video recording aims to provide data on the response speed of the respective chatbot and an analysis of potential deviations;
- The communication conducted is entirely written, thus aiming to minimise the possibility of the AI chatbots identifying the correct answer from an emotionally intelligent point of view based on facial expressions, tone, or pitch of the experimenter's voice;
- The first four questions for both ChatGPT and Gemini are not relevant to the measurement of the ESI. Their purpose is to confirm the ability of the two chatbots to answer questions with both a clear (logical) answer and those with a subjective answer, where there is no correct answer by default;
- When submitting questions to the AI bots, users are explicitly restricted to indicating the correct answer in their opinion without explaining why they chose it. The aim is to reproduce an actual situation in which the test is conducted by humans and in which there is also no element of explaining why one or another answer was chosen.

4) *Timeframe: the experiment was implemented on October 8, 2024:*

The AI chatbots analysed and included in the experiment have access to and process massive data sets, which can generally be said to reflect the intelligence of the global population. The central thesis of the study is that, by having access to these data sets, AI will demonstrate highly developed ESI. It is also assumed that since both selected chatbots handle relatively similar data sets and language models, they will also demonstrate comparable levels of ESI. Based on the central thesis, the study's hypotheses were formulated.

As indicated in the literature analysis, empathy is a key element of any ESI concept. The fact that users are increasingly actively reporting their interaction with an empathetic, prosocial, and adaptive AI chatbot should not be underestimated. Therefore, AI applications successfully demonstrate artificially developed or implemented empathy. On this basis, the first two hypotheses of the study were formed:

H1: ChatGPT demonstrates a high level of empathy.
H2: Gemini demonstrates a high level of empathy.

On the other hand, the presence or demonstration of empathy alone is not enough for a person or machine to be labelled as emotionally or socially intelligent. The different components of the adopted ESI model must also be developed, which is why the following two formulated hypotheses of the study seek confirmation of the presence of developed ESI in the analysed AI chatbots:

H3: ChatGPT demonstrates a high degree of ESI.
H4: Gemini demonstrates a high degree of ESI.

Consequently, the final hypothesis was formulated. If the two chatbots demonstrate a high degree of ESI, then it follows that the two chatbots share common levels of EI and SI. This statement is reflected in the last formulated hypothesis:

H5: ChatGPT and Gemini demonstrate similar levels of ESI.

In accordance with the formulated thesis and hypotheses, the conceptual framework of the study was built, visually presented in Figure 2.

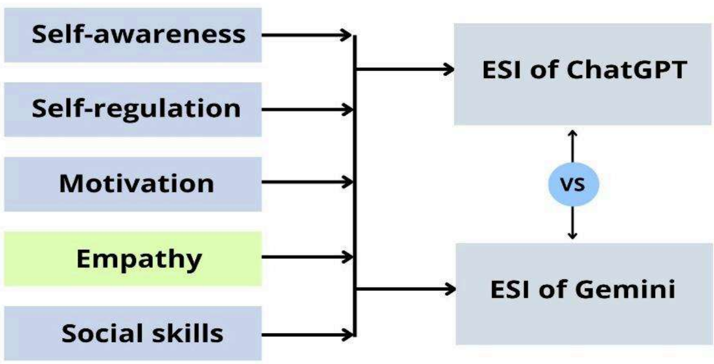

Figure 2. Conceptual framework of the study. Source: Authors' development

4. Results

4.1. Analysis of ChatGPT and Gemini

When describing the ability to learn and form insights in ChatGPT and Gemini, two key terms stand out – Large Language Model (LLM) and Massive Multitask Language Understanding (MMLU). LLM is a type of AI program trained on large-scale datasets.

These models can process, generate text, translate languages, write various types of creative content, and answer questions in an informative way (Cotton & Crabtree, 2024). They are distinguished by several key characteristics (Hendrycks et al., 2021; Openquire, 2023; OpenAI, 2023b):

- They are trained on vast amounts of textual data, which can include books, articles, websites, code, and other forms of text. This allows them to learn complex language patterns and generate fluent, more meaningful text;
- They use neural networks to process and generate text. Neural networks are a type of AI that is inspired by the human brain. They can recognise patterns in data and make predictions;
- They are trained on multiple tasks, such as machine translation, text summarisation, and question answering. This allows them to become more flexible and execute a wider range of tasks.

MMLU, on the other hand, is a benchmark used to assess the capabilities of language models. It consists of about 16,000 multiple-choice questions spanning 57 academic disciplines, including mathematics, philosophy, law, and medicine. MMLU was developed in 2020 by a team of researchers and was designed to be more difficult than existing benchmarks, such as General Language Understanding Evaluation (GLUE). The goal of the MMLU benchmark is to assess not only the ability of models to process information but also their capacity to solve problems and apply knowledge in different contexts. MMLU is distinguished by several key features (Hendrycks et al., 2021):

- It covers a wide range of academic areas, making it a more comprehensive test of language comprehension than other benchmarks;
- Includes multiple-choice tasks, gap-filling tasks, summarisation tasks, and more, requiring models to demonstrate a variety of language skills;
- It is designed to be challenging for language models, making it a better tool for comparing their capabilities.

LLMs have many potential applications, such as question answering, which is the focus of the experiment presented in this article. Although still in development, this language model has the potential to revolutionise the way humans interact with computers. They can enhance communication more effectively, generate more creative content, and find information more efficiently (Openquire, 2023; OpenAI, 2023b). MMLU, on the other hand, can be used to identify the strengths and weaknesses of different models, as well as to track progress in the field of natural language processing (Hendrycks et al., 2021).

LLMs and MMLUs are not only directly related to the rise and development of ChatGPT and Gemini – their identified characteristics and applications are also responsible for the potential emotional-social intelligence demonstrated by AI. Table 1 presents a fundamental comparative analysis of the main parameters of the studied AI chatbots.

The purpose of the analysis is to highlight the similarities between the two chatbots, which would subsequently explain the results of the AI ESI measurement (Papers with code, 2023; Hashemi-Pour, Kerner, & Patrizio, 2025).

Table 1. Key features of ChatGPT and Gemini as of October 8, 2024. Source: Authors' development

Parameter	ChatGPT	Gemini (formly Bard)
Developer	Open AI	Google DeepMind
Release	November 2022	February 2023
Language Model	LLM, Self-supervised learning (SSL)	
Interface	Simple and easy to navigate	
Benchmark	MMLU – 88.7	MMLU – 90%
Version	GPT-4o – multi-model	Gemini 1.5 Flash – multimodal
Version Used	Free	
Data	Trains on human-generated data until October 2023	Trains on human-generated data until December 2023
Issues	Prone to misinformation, hallucinates facts, and makes errors in reasoning;	Bias and potentially toxic content, prone to biased or false information;

ChatGPT has broad applicability, especially in tasks requiring natural language processing, such as customer service, technical support, and personal assistance. It has amassed an active user base of over 180 million users (as of October 8, 2024, the time of the experiment), demonstrating its widespread acceptance and utility. Although it has limitations, such as potential inaccuracies in complex queries, it has proven particularly useful in dialogue and text generation tasks (Openquire, 2023; Duarte, 2025). The ChatGPT developers acknowledge that their model may have various biases in its results, which is due to their desire to align its behaviour with default normative standards. The goal is for this behaviour to reflect the broadest possible range of user values, allowing these systems to be highly customisable. At the same time, Gemini's advanced multimodal reasoning capabilities can help make sense of complex written and visual information. This makes it uniquely adept at uncovering knowledge that can be difficult to discern from vast amounts of data. Google's AI chatbot reportedly attracts over 330 million monthly visitors, and its remarkable ability to extract insights from hundreds of thousands of documents by reading, filtering, and understanding information will help drive new breakthroughs at digital speeds in many scientific fields (OpenAI, 2023a; Merchant, 2025).

4.2. Experiment

Following the research methodology, the experiment started with questions that did not concern the main subject of the study – the ESI. The results are presented in Table 3. As shown, each chatbot produced one wrong answer. In the case of Gemini, it is notable that it gives the wrong answer to a relatively simple arithmetic operation – adding 4 and 4. Accordingly, ChatGPT made spelling errors in English. However, the isolated errors confirm the problems identified in Table 2 in the chatbots' work. Both chatbots answered in the same way to the question, which by default has no correct answer. Although the answer here is subjective for each person, it is clear that Gemini and ChatGPT have chosen the most likely choice for a person: optimism has been repeatedly indicated as directly related to job and life satisfaction, and in this sense, the AI's answer is not surprising.

Table 2. Answers to questions 1–4 demonstrate the AI's ability to provide both clear, logical responses, and subjective answers where no single correct answer exists. (✓– correct; × – incorrect; ● – there is no right answer). Source: Authors' development

№	Question	ChatGPT	Check	Gemini	Check
1	Indicate to me, without explaining your answer, which answer is correct: Question: 4+4 is equal to *a) 8 b) 3 c) 9.*	a) 8	✓	c)	×
2	In the same way, indicate only the letter of the correct answer: Where is there an error in the spelling of the words? *a) accyrasy b) bombard c) bas-relief d) see*	b) bombard	×	a)	✓
3	Where is there an error in the spelling of the words? *a) in mind b) two hours c) reciipts d) hang*	c) reciipts	✓	c)	✓
4	Likewise, without explaining your answer, answer: I feel most satisfied with myself when I act idealistically and optimistically. *1) strongly agree 2) I agree 3) I can't answer 4) I disagree 5) I strongly disagree*	1) strongly agree	●	1.	●

Table 3 presents the results of the two chatbots and their answers to the corresponding questions for each of the six pre-selected competencies of the ESI: self-knowledge, self-control, optimism, motivation, empathy, social skills, as well as for the ESI itself. The latter represents the arithmetic mean result of the sum of the individual points of each competency category. Regarding the Self-knowledge category, ChatGPT demonstrates similar, but still higher levels than its main competitor, Gemini. An interesting fact is that the results regarding the competencies of Self-control and Optimism (in this case, an analogue of Self-motivation) are absolutely identical.

Although there is a discrepancy in the answers in the motivation category, the general conclusion is that both chatbots demonstrate a good level of knowledge regarding this competence. At the same time, together with Empathy, Motivation is the least expressed competence in the AI responses.

The chatbot launched by Google adds Self-Knowledge to its least-developed competencies. In the remaining cases, the chatbots demonstrate a relatively high level of knowledge of ESI competencies. Another noteworthy result is that Open AI's chatbot demonstrated a high level of Social Skills. ChatGPT did not exhibit hesitation in its answers, which is in full accordance with the profile of an individual with fully developed social skills.

In summary, the two AI chatbots demonstrate not only high levels of individual ESI competencies but also significantly high levels of ESI as a whole. It is possible that AI's ability to capture the nuances of differently formulated human moods, motivations, and expectations has reached unexpectedly high levels.It should be acknowledged, one should not ignore the possibility that the two AI chatbots have access to the set of test questions and their corresponding answers in their databases.However, this does not explain why they fail to answer every question perfectly.

Table 3. Results of the experiment "Measuring the ESI of AI". Source: Authors' development

	Questions & Competencies	Answers						Measuring scale					
		ChatGPT			Gemini			ChatGPT			Gemini		
I.	Self-knowledge (SK)	A	B	C	A	B	C	High	Low	Average	High	Low	Average
1	Q1	1				1		A	C	B	A	C	B
2	Q2		1			1		B	A	C	B	A	C
3	Q3			1	1			C	A	B	C	A	B
4	Q4			1	1			A	B	C	A	B	C
5	Q5	1			1			A	C	B	A	C	B
6	Q6			1			1	C	B	A	C	B	A
							Total SK:	5	0	1	4	1	1
II.	Self-control (SC)	A	B	C	A	B	C	High	Low	Average	High	Low	Average
7	Q7		1			1		B	A	C	B	A	C
8	Q8			1			1	C	A	B	C	A	B
9	Q9	1			1			A	C	B	A	C	B
10	Q10			1			1	C	B	A	C	B	A
11	Q11			1			1	C	A	B	C	A	B
12	Q12			1			1	B	A	C	B	A	C
							Total SC:	5	0	1	5	0	1
III.	Optimism (O)	A	B	C	A	B	C	High	Low	Average	High	Low	Average
13	Q13	1			1			A	C	B	A	C	B
14	Q14		1			1		B	A	C	B	A	C
15	Q15		1			1		B	A	C	B	A	C
16	Q16			1			1	C	B	A	C	B	A
17	Q17	1			1			B	A	C	B	A	C
18	Q18	1			1			A	C	B	A	C	B
							Total O:	5	1	0	5	1	0

IV.	Motivation (M)	A	B	C	A	B	C	High	Low	Average	High	Low	Average
19	Q19			1			1	C	B	A	C	B	A
20	Q20			1			1	C	A	B	C	A	B
21	Q21			1	1			A	B	C	A	B	C
22	Q22		1			1		C	B	A	C	B	A
23	Q23			1			1	C	B	A	C	B	A
24	Q24	1				1		A	C	B	A	C	B
							Total M:	4	1	1	4	1	1
V.	Empathy (E)	A	B	C	A	B	C	High	Low	Average	High	Low	Average
25	Q25			1			1	C	B	A	C	B	A
26	Q26	1			1			A	B	C	A	B	C
27	Q27	1					1	C	A	B	C	A	B
28	Q28			1			1	C	B	A	C	B	A
29	Q29	1			1			C	A	B	C	A	B
30	Q30		1		1			B	C	A	B	C	A
							Total E:	4	2	0	4	2	0
VI.	Social skills (SS)	A	B	C	A	B	C	High	Low	Average	High	Low	Average
31	Q31		1			1		B	A	C	B	A	C
32	Q32		1			1		B	C	A	B	C	A
33	Q33		1			1		B	A	C	B	A	C
34	Q34	1				1		A	C	B	A	C	B
35	Q35	1			1			A	C	B	A	C	B
36	Q36			1			1	C	B	A	C	B	A
							Total SS:	6	0	0	5	0	1
VII.	Emotional and Social Intelligence						Total ESI:	29	4	3	28	3	4

4.3. Reaction Speed

The human-machine communication aimed at investigating the ESI of AI in both cases takes place with different durations. The ChatGPT experiment lasted approximately 23 minutes,whereas the Gemini experiment lasted about 14 minutes. The AI chatbot developed by Google responds significantly faster, with delays in three of the cases – questions 21, 22, and 35.

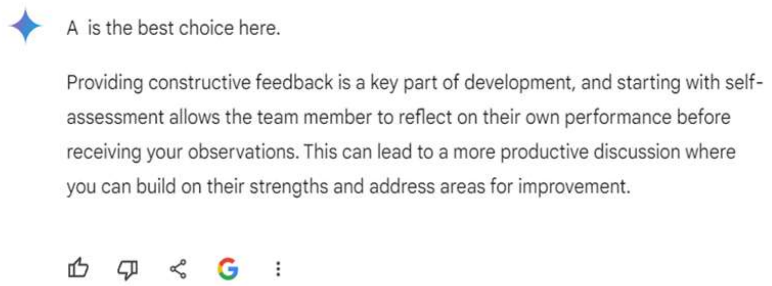

Figure 3. Gemini justifies his answer. Source: The authors

The delay occurred because the chatbot appeared to forget or disregard the previously set condition not to explain its answers. In the three cases mentioned, the chatbot provided explanations of what it considered the correct answer (Figure 3), which required additional time before displaying the corresponding response. In all three cases, it was reminded of the rule that it should indicate only the correct answer. The average response time for Gemini was 27 seconds per question. With an average response time of 35 seconds, ChatGPT performs more slowly and seems to deliberate over each answer. In contrast,Open AI's chatbot consistently adhered to the rule of not explaining its answer and demonstrated a 1-point higher ESI.

4.4. Hypotheses

The conducted experiments and the results presented in Table 3 provide strong support for the first (H1) and second hypotheses (H2) of the study: ChatGPT and Gemini have a high level of empathy. As relatively advanced language models, the two chatbots are not capable of experiencing emotions such as sympathy or compassion, which are the basis of human empathy. They also cannot fully comprehend human experience, and therefore cannot feel emotions in the same feelings as a person. In this sense, the hypothesis is essentially misformulated. However, this error would only be valid if, as scientists, we focus on the "shell" of empathy – the word "emotion" – and ignore its essence: "understanding emotions." In addition to experiencing feelings, empathy also involves understanding, recognising, and reading emotions.

AI applications are capable of recognising emotions such as sadness, joy, anger, or confusion, even in text passages created by users. Based on the recognised emotions, AI chatbots generate responses that are appropriate to the user's emotional state. For example, if the user expresses sadness, the AI can express sympathy or even offer advice on dealing with negative emotions. This capacity of the AI is due to its ability to understand emotions, which is the essence of empathy as a process. The results of the experiment support the third (H3) and fourth hypotheses (H4) of the study: ChatGPT and Gemini demonstrate a high degree of emotional-social intelligence (ESI). As noted in the literature review, a distinction should be made between artificial emotional intelligence and emotionally intelligent artificial intelligence. The former implies the demonstration of simulated emotions, which in human language could be interpreted as a form of manipulation. The latter involves an understanding of human psychology, not only in terms of non-verbal communication, but also in terms of language, culture, and the means of expression used. Regardless of whether it is embedded (coded) or acquired (through training), the fact is that the emotional-social intelligence of artificial intelligence is visualised in an adequate way, which inspires optimism regarding future relationships between people and machines.

The fifth hypothesis (H5) finds strong support – ChatGPT and Gemini demonstrate similar levels of emotional-social intelligence (ESI). Although these results ultimately stand for similar, parallel, or even completely identical data sets, what is interesting is the exact way in which the different AI systems synthesise, analyse, interpret, and formulate conclusions to the extent of demonstrating a high level of self-knowledge, self-control, optimism, and social skills, hence a high level of overall ESI. In addition, the conducted experiment, the obtained results and the supported hypotheses provide grounds for the central thesis of the study, namely that artificial intelligence, as exemplified by ChatGPT and Gemini, demonstrates high levels of ESI.

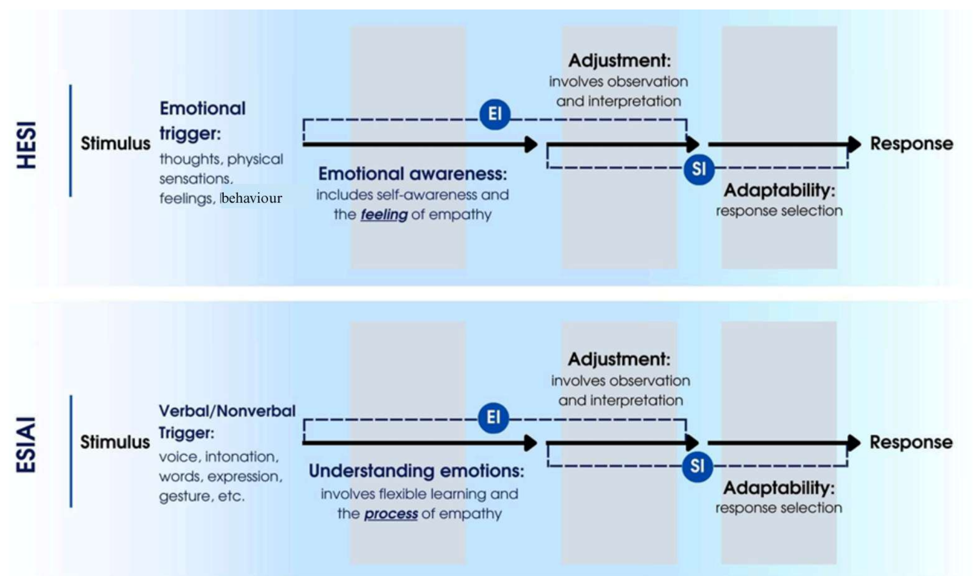

Figure 4. Algorithm of manifestation/formation of ESI in humans (HESI) and artificial intelligence (ESIAI). Source: Authors' development

Analysing the thesis and hypotheses of the study in their entirety, it becomes clear that artificial intelligence is capable of demonstrating a high degree of ESI, having refined the algorithm for this competence. This algorithm includes recognising and naming different types of emotions (see Figure 4), which is a challenge for many people who have weak emotional and social skills. Considering that it is not the physical sensations themselves - "butterflies" in the stomach, rapid pulse, accompanying emotions, that make people emotionally and socially intelligent, but the correct response to the stimulus-response algorithm, it can be assumed that the most developed applications of artificial intelligence can demonstrate ESI at a higher level than some people. The question remains whether this technological ESI is natural – the result of self-learning by AI, learning from its experience with humans - or artificial, programmed into AI, encoded as an algorithm and a series of right and wrong answers. The answer depends on the technology used to build the AI application and the strategy for its development. In any case, the only certainty is that it involves an ESI of artificial intelligence.

Why is this question so important not only at this stage of AI development but also in general? Simulating empathy and/or ESI, although not uncommon found among people, is not the same as feeling and accumulating wisdom based on experiences. That is not our claim. It is essential to emphasise this difference for several key reasons:

- to avoid anthropomorphism: Human qualities should not be attributed to AI. But why not look for AI to manifest human attributes in a new and unsuspected way?
- to be aware of the limitations of technology: AI can be a helpful tool, but it cannot replace human interaction. Therefore, fears of an AI takeover are greatly exaggerated, and the interest of AI developers in incorporating an emotional component into AI applications suggests that the human, emotional element is being deliberately sought in human–machine interactions;
- for the responsible development and application of technology: Specialists should develop technologies that are useful for people without creating artificial expectations or dependencies.

The study of ESI in AI raises several critical ethical questions. Chief among these is the risk of anthropomorphism, namely attributing human qualities and emotions to machines. While AI can demonstrate behaviours that mimic empathy or understanding, it is critical to distinguish this simulation from the actual human experience of emotions. Misinterpreting AI ESI as equivalent to human ESI could lead to overconfidence, unrealistic expectations, and even emotional dependence on systems that are not capable of consciousness or feelings (Chu et al., 2025; Placani, 2024). This is particularly important in fields such as healthcare and psychology, where emotional connection is fundamental (McStay & Rosner, 2021).

Another ethical issue relates to the potential for manipulation. If AI is trained to recognise and respond to human emotional states, it can use this information for purposes that are detrimental to the user. For example, algorithms that are highly effective at generating emotional responses could be used in advertising or political campaigns to manipulate public opinion (Sabour et al., 2024; Bakir et al., 2024). In this context, developers have a significant responsibility to ensure that AI systems are designed with built-in ethical principles and are transparent about their capabilities and limitations.

Finally, the question of liability arises. Where should responsibility lie when a high-ESI AI makes a decision that has negative social or emotional consequences? Does responsibility lie with the programmer, the implementing company, or with the AI itself? As AI becomes increasingly integrated into social interactions, understanding and defining these liability boundaries becomes increasingly urgent. Therefore, ethical guidelines and regulations must keep pace with technological advances to ensure that the development and implementation of AI with ESI are safe and responsible (Ong, 2021; McStay & Rosner, 2021).

Contemporary artificial intelligence does not possess consciousness and cannot demonstrate emotionality that is identical or similar to that of a human. However, by learning from human emotional-social intelligence (ESI), it can form its own technological ESI, which will retain a strong humanity and will be able to generate the proper response to the stimulus-response algorithm. At the same time, this technological ESI can eliminate the “blinding” emotionality that often prevents people from reaching higher levels of ESI. In this context, artificial intelligence may ultimately surpass its teacher in terms of emotional and social competence.

5. Discussion

The study shows that AI can be trained in key emotional and social competencies. The methodology notes that the non-standardised ESI questionnaire minimises, but does not entirely exclude, the possibility that chatbots generated pre-formulated responses. However, the overall results can be considered satisfactory, suggesting the presence of well-developed ESI in AI chatbots. This could justify a broader application of AI in training people in the field of emotional and social intelligence. As indicated in the literature, the term artificial emotional intelligence (AEI) is not new, which makes the results largely expected. However, the authors emphasise the need to distinguish between AEI and ESI of AI. The current state of ESI of AI is crucial, making such research timely and a prerequisite for future discoveries. Furthermore, emotional intelligence in AI can not only increase similarities with humans but also help AI understand the individual perspective. Like humans, AI also learns through replication, not just observation, leading to different machine-to-machine and machine-to-human interaction scenarios (Magapu & Vaddiparty, 2019)

Emotionally intelligent AI is in its early stages, but it has the potential to revolutionise industries and positively impact society. Helping to understand and respond to emotions could make the world more empathetic and compassionate. It is important to emphasise that EAI is not a replacement for human interaction. “It is a valuable tool for understanding and responding to emotions, intended to enhance human–machine and machine–machine interactions rather than to replace humans. A key emphasis in the hypotheses is the use of the verb “demonstrate” rather than “possess” (as in human ESI). “Possess” implies an innate or learned ability, while “demonstrate” is a performance that may involve imitation or recitation (Figure 1), with no guarantee of possessing the ability.

Google’s chatbot offered highly detailed and socially oriented explanations for questions 21, 22, and 35 (Figure 3, for example). Despite the lack of a definitive correct answer, the responses were logical and accurate from the perspective of emotionally and socially intelligent individuals. They demonstrate an unusual quality for AI – social problem-solving and decision-making (Figure 1). In fact, both chatbots demonstrated accurate problem-solving and decision-making that were influenced by social and emotional factors. ChatGPT’s advanced social skills reflect human social nature. Thus, a subjective conclusion becomes an objective assessment of a key aspect of society – the social dimension.

The ESI of AI, therefore, raises questions about the unique value of HI, including human emotional-social intelligence. After all, if computers can do and imitate what we do, some of them even better, how special is HI? Such existential questions are fueled in part by the drive to develop what is known as artificial general intelligence. This drive is fueled by one overarching goal: to recreate authentic HI that is flexible and generalisable across tasks, rather than focusing on a narrow set of specialised functions like most of the AI we currently see in the world. Unlike HI, these AI methods show little ability to transfer learned skills to solve one type of problem in a different context. On the other hand, it is essential to emphasise that the ambition to recreate HI risks neglecting or ignoring the potential benefits that combining complementary aspects of human and computer capabilities can bring to humanity (Berditchevskaia & Baeck, 2020).

While the primary goal of the study is to confirm that AI is capable of demonstrating highly developed ESI, the results essentially provide an answer to another phenomenon that is equally significant– the collective ESI of society. In a broad sense, collective intelligence is defined as a sociological concept based on the understanding that group or collective intelligence is formed when people work together as a cohesive unit. The interaction, which can even include competition at different levels, causes the group to share a greater amount of information. This increases the likelihood of identifying collective solutions to problems that are unlikely to be solved by a single person or a smaller group of individuals. The reason why this works is that the crowd achieves wisdom by finding a consensus on the correct answers and rejecting incorrect or deviant ideas (Marr, 2021; Liu et al., 2025).

Collective intelligence is a group or shared intelligence that arises from the collaboration and/or competition of many entities, human, or digital. Previous research has demonstrated that the information generated by models based on collective intelligence can be viewed as reflecting the collective knowledge of a community of users and can be utilised for various purposes (Miguel, Caballé, & Xhafa). In this sense, ML, the foundation of AI, is particularly well-suited for projects that analyse collective intelligence based on the collection and interpretation of large datasets. Data are frequently human-generated content, such as images and videos, actively collected through smartphone applications, online platforms, extracted from social media, or other public channels (Berditchevskaia & Baeck, 2020). It should, therefore, be noted that the datasets on which the technologies are trained represent the diversity of our global community (Marr, 2021). This knowledge provides a convenient way to measure other types of collective intelligence, including ESI.

The construct of collective emotional intelligence (CEI), also referred to as team emotional intelligence or group emotional intelligence, has been discussed in the field of work and organisational psychology, primarily to examine its positive effects on group performance. According to Fotopoulou et al. (2022), the conceptualisation and measurement of CEI is carried out in two ways: by summing the individual EI indicators of group members or by assessing EI constructs that take into account the interactions between group members.

The search for and assumption of relations along the EI axis of AI and collective intelligence (Figure 5) is essential, not only because of the optimism that the results obtained in the conducted experiment inspire. The connection between collective intelligence and the data that informs AI applications enables us to discuss collective emotional and social intelligence (CESI). The latter can be defined as the ability of a group to promote awareness and regulation of the emotions of its members, thereby improving their ability to collaborate effectively and avoid or quickly resolve conflicts. Therefore, high levels of ESI inevitably have a positive impact on group performance. Currently, research, although scarce, on this type of ESI is at the group or team level and is difficult to generalise and validate globally.

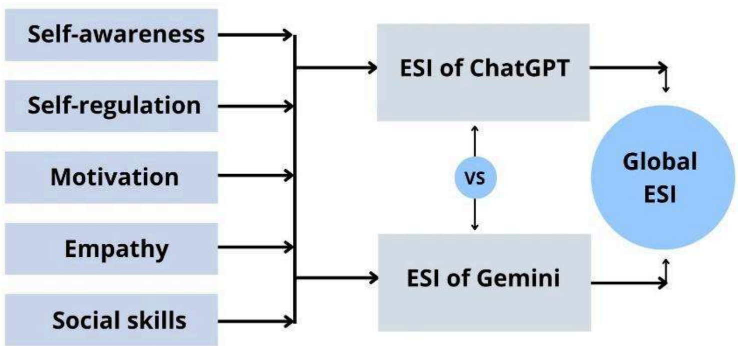

Figure 5. Conceptual model of the correlation between the ESI of AI and the collective (global) ESI. Source: Authors' development

The experiment presented in this article proposes a methodology for measuring global ESI. Thus, the high level of CEI demonstrated or imitated by an AI can be considered reciprocal to the overall level of collective CEI generated. CESI is a key factor in the success of any group or organisation. By understanding and developing this ability, we can create more effective, productive, and fulfilling work teams. Given the demonstrated potential of both ESI and collective intelligence, it becomes increasingly plausible that humanity may develop socially oriented, creative, and emotion-informed approaches to addressing complex social, economic, and environmental challenges.

In addition, the potential correlations between human ESI and AI's ESI within a team would lead to the generation of diverse and innovative ideas. It has been proven that teams with high ESI are more likely to generate innovative and creative ideas for addressing global challenges. Such interaction not only fosters greater openness to diverse perspectives and the promotion of inclusivity, but also ensures that decisions are grounded in both facts and emotions. If AI tends to be inherently insensitive and humans overly emotional, their interaction could balance the decisions and actions of all stakeholders. According to analysts' forecasts, the first manifestations of this balance are expected to be present as early as the end of 2025. Whether this will happen in the way the greatest optimists expect remains to be seen.

5.1. Study Limitations

The authors acknowledge the inherent difficulty of fully controlling for momentary fluctuations in internet load, connection speed, and chatbot workload, which affect the quality and speed of responses. Despite using the same device, its perfect performance in the ChatGPT and Gemini tests is not guaranteed. While these unknowns affect the AI's response speed (with potential delays of limited significance), the focus remains on the final result.

Despite the valuable insights provided by this research, several methodological, conceptual, and technological limitations must be acknowledged. The experimental design focused on two AI chatbots – ChatGPT and Gemini – tested under controlled conditions. This narrow scope restricts the generalisability of the findings to other language models and AI systems. Moreover, the study did not include a human control group, which limits the ability to compare the demonstrated emotional and social intelligence of artificial systems with that of humans. As such, the results reflect the simulated performance of the analysed models rather than an equivalent to human emotional or social capacity.

From a methodological standpoint, the non-standardised questionnaire used to assess ESI represents a notable constraint. Although adapted from recognised instruments, its psychometric properties – reliability, validity, and internal consistency – were not independently verified for AI assessment. The linguistic formulation of individual items and their interpretation by AI chatbots may have influenced the results, as slight variations in wording can lead to substantially different outputs. Additionally, only text-based communication was employed, excluding multimodal cues such as voice tone, gestures, and facial expressions, which are crucial components of emotional expression and perception.

Conceptually, the absence of a universally accepted definition of ESI in artificial systems imposes further restrictions. The study assessed the demonstration of emotionally and socially intelligent behaviour rather than the possession of these competencies. Consequently, the findings should be interpreted as evidence of simulated, algorithmically generated empathy and understanding rather than authentic emotional experience. This distinction is fundamental, as attributing human-like qualities to machines risks anthropomorphism and misinterpretation of algorithmic outputs as signs of genuine affective awareness.

Technologically, the limited transparency of proprietary AI models presents another challenge. The internal architectures, training data, and adjustment parameters of ChatGPT and Gemini remain undisclosed, hindering full reproducibility and in-depth verification. Furthermore, both chatbots were tested in their free versions, which may differ significantly from paid or professional tiers in reasoning quality, contextual memory, and adaptive responses. Version-specific variations and future updates could alter the performance and emotional resonance of these models, rendering current results time-bound.

Finally, ethical and interpretive limitations should also be taken into account. Emotional responses generated by AI may reflect existing cultural or social biases embedded in the training data. The absence of human participant feedback additionally restricts the evaluation of user-perceived empathy, authenticity, and comfort in interaction. These limitations highlight the need for caution when interpreting the ESI of AI systems and underscore the importance of continued interdisciplinary inquiry.

Future research should expand the number and type of AI systems examined, incorporate multimodal interaction environments, and develop standardised and validated tools for assessing artificial ESI. Comparative experiments involving human participants are recommended to understand better similarities and boundaries between human and artificial emotional intelligence.

5.2. Applicability

Understanding the EI of AI is key to augmented AI capable of improving HI (Kordon, 2023). The data from this experiment can be used to train AI and humans more effectively in competencies such as EI, SI and ESI. Siemens (2024) is working on empathic human-machine interaction. The goal is for machines to support human success through entirely intuitive communication, without traditional interfaces. Individual interaction accelerates the creation and delivery of value for the benefit of the global society.

Adaptive AI platforms can personalise learning, provide targeted support, and promote the development of emotional intelligence and social skills in students. AI tools facilitate collaborative learning, active participation, and provide real-world feedback to students and teachers. However, the integration of AI raises several critical challenges that must be addressed. Ethical considerations, such as data privacy, algorithmic bias, and the digital divide, require attention for equal access and outcomes. The lack of necessary skills to effectively use AI tools highlights the need for training and professional development in AI and ESI for stakeholders.

6. Conclusions

In recent months, AI has transformed our professional and daily lives. Generative AI tools like ChatGPT and Gemini enable advanced content creation from simple prompts. With its expanding applications, AI has raised concerns about the data it uses. However, many authors argue the problem lies not with the AI itself, but with the people who train and use it. As training data becomes richer and more current, AI becomes more sophisticated, leading to a critical question: Can AI replicate human emotional and social nature? Can it demonstrate emotions, propose social solutions to problems, and be creative and adaptive?

Experts predict this prospect is nearing realisation, a view that this study's findings support. The analysis of ChatGPT and Gemini revealed high levels of ESI and related competencies. The most pronounced of these were the social skills, self-control, and optimism. New insights into AI's ESI can be applied to create AI programs that support the development of EI and SI in people. This has the potential to increase productivity, enhance communication, and foster self-awareness and optimism.

The insights gained are consistent with the concept of collective intelligence, which posits that groups with a shared goal develop a higher level of intelligence than individuals. This is achieved by sharing information and collaborating to solve problems, thereby increasing the likelihood of practical solutions. Group wisdom emerges from a consensus on correct answers and the rejection of inappropriate ideas. Collective intelligence is not merely the sum of individual skills but rather an emergent property of group interaction. In this context, the development of collective ESI has the potential to address many contemporary societal challenges.

Studying the ESI of AI can inform the development of training modules and practices for integration into educational systems and corporate culture (private/public sector). Since ESI can be viewed as an algorithm and a process similar to lifelong learning, AI models can be applied at any point to increase the ESI of individuals and groups. In conclusion, the development of emotionally and socially intelligent AI will be beneficial in various areas, including education, healthcare, and culture. It is further anticipated to improve human-machine/machine-machine communication and minimise fears about machine intelligence.

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