

# Differentiated Modelling of Emotions by Artificial Intelligence: A Comparative Analysis of GPT, Deepseek and Gemini

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## Abstract

This article presents an exploratory study on how three generative artificial intelligence models – ChatGPT (GPT), Deepseek (DS) and Gemini (GEM) – highlight emotions in a stock market simulation context. The aim is to compare the evolution of the emotional profiles produced by these models based on queries representing increasingly emotionally charged situations. These queries are part of a progressive sequence: a semi-structured post-experiment interview (Q1), consideration of simulated stock market performance (Q2), a market configuration perceived as negative (Q3), the introduction of a gender factor (Q4) and the addition of a competitive element linked to a financial reward for students (Q5). The AI responses were analysed using an emotional typology based on nine emotions (fear, happiness, sadness, optimism, disgust, positive surprise, negative surprise, positive anticipation, negative anticipation) associated with their affective valence. The data were then studied according to a dual logic: counting the emotions by AI and by query and evaluating the dominant or ambivalent emotional valence of each response. The results highlight significant differences between the models. GPT adopts an overall pessimistic emotional profile, characterised by a high recurrence of fear and negative anticipation. GEM follows a similar trend, although slightly more nuanced. Conversely, DS exhibits more ambivalent pattern, articulating positive and negative emotions within a more contrasting dynamic. Beyond the inter-model comparison, the study highlights the importance of parallel human reading in the interpretation of emotional productions. It emphasises the need for a critical approach to assessing the consistency, relevance and contextualisation of the affects produced by AI, particularly in simulated environments. This research thus opens perspectives on how AI can potentially be integrated into emotional analysis or mediation systems and calls for interdisciplinary dialogue between communication sciences, affective sciences and artificial intelligence development.

**Keywords:** QUALITATIVE RESEARCH, ARTIFICIAL INTELLIGENCE, EMOTIONS, STOCK MARKET, INDIVIDUAL INVESTORS

## 1. Introduction

Understanding emotions in simulation contexts is a central issue for many disciplinary fields, ranging from communication sciences to social psychology, cognitive sciences and artificial intelligence. Far from being mere epiphenomena, emotions play a structuring role in decision-making dynamics, particularly when an individual is confronted with uncertain, competitive or symbolically high-stakes environments.

In the field of simulated systems, our work has helped to highlight the structuring role of emotions in situated interactions. We have demonstrated that emotions do not merely accompany action: they organise its dynamics by influencing the way actors interpret a situation, engage with it or distance themselves from it. In our research on decision-making processes in simulated environments, we emphasise how supervisory mechanisms, instructions and social expectations frame and channel emotional expression, giving rise to specific forms of scripted emotions (Finet et al., 2025d; Finet et al., 2025e).

This relational and contextualised conception of emotions raises an increasingly important question: how do generative artificial intelligences highlight emotions in similar analytical contexts? In other words, to what extent can linguistic models produce emotional responses that are consistent, credible and stable over time?

This article proposes to answer this question through an experimental protocol based on five successive queries, inspired by simulated trading situations, ranging from a simple post-experience interview to increasingly emotionally specific configurations, including performance pressures, financial stakes and elements of social differentiation. The objective is twofold:

- on the one hand, to analyze the emotional responses produced by three AIs (GPT, DS, GEM) when faced with these increasingly intense emotional contexts;
- on the other hand, to compare these productions by mobilizing frameworks derived from the analysis of emotions, cognitive biases and communication simulation.

By combining these two dimensions, our objective is to further the discussion on the fabrication of emotions in supervised systems.

## 2. Literature Review

### 2.1. The Affective Turn in the Social Sciences

Long relegated to the realm of the irrational, emotions have gradually been rehabilitated as scientific objects. Since the 1980s, a body of work has contributed to an affective turn in the social sciences, re-examining the classic categories of action, judgement, rationality and power. Authors such as Hochschild (1983), Illouz (2006) and Ahmed (2004) have shown that emotions are both socially constructed and politically situated.

This shift has led to a renewal of objects and methods: emotions have been considered as drivers of action, vectors of meaning and indicators of social positioning. Sociology, anthropology, social psychology and

language sciences have thus converged towards an approach to emotions as discursive, interactional and embodied phenomena. In this context, the study of emotions expressed in semi-structured interviews is gaining legitimacy and complexity.

## **2.2. Emotion in Discourse: Forms, Functions and Ambivalences**

In interviews, emotions are not directly apparent. They are often intertwined in discourse, inferred from tone, pauses, hesitations, or reconstructed retroactively by the speakers. Emotion can appear as a narrative break, an accentuation, a strategy of affiliation or distancing. It is rarely stable, unambiguous or isolatable.

Several studies (Plantin, 2011; Traverso, 2009) have highlighted the affective polyphony that characterises everyday discourse: a single sequence can involve several contradictory emotions (guilt mixed with pride, relief tinged with anxiety). The semi-structured interview setting, structured by the guide, follow-up questions and the interviewer's position, strongly influences the way in which emotions are expressed or avoided.

This instability, which is specific to the interview format, makes emotional analysis particularly delicate: it requires attention to the dynamics of interaction, lexical choices, but also to what is left unsaid. Emotions are often rephrased, justified after the fact, or shifted onto a third party ("people were afraid" instead of "I was afraid"). This vagueness necessitates a nuanced analytical approach and makes any attempt at automatic classification without safeguards uncertain.

## **2.3. Recognising Emotions in Texts: a Linguistic, Cognitive and Computational Task**

The recognition of emotions from textual data has emerged at the intersection of computational linguistics, cognitive psychology and automatic natural language processing. Since the 2000s, lexical approaches have attempted to detect emotions using dictionaries that associate words with emotions (e.g. NRC Emotion Lexicon). These methods, often applied to social networks, have two major limitations: they are based on lexicons that are taken out of context and ignore the syntactic structures, inferences and implicit registers of language.

The advent of transformer-type models and, more recently, generative language models (LLMs) has opened up new possibilities: these models can not only identify an emotion, but also provide contextual justification, taking into account the style of expression or the situation described. However, these models still face major challenges (Deng & Ren, 2021; Ziems et al., 2023):

- the porosity of emotional boundaries (e.g., sadness versus disappointment),
- the incompleteness of clues in non-standardised texts (interviews, testimonials, narratives),
- the effect of the prompt, the model chosen, and the level of constraint imposed on the outputs generated.

Empirical work from articles *NPG 1–3* confirms this variability: LLM models are effective at detecting a dominant valence and identifying primary emotions, but fail to produce stable fine-grained combinations

between models or to handle implicit interactional dimensions (e.g., irony, euphemism, discursive positioning).

#### **2.4. Towards assisted Emotion Analysis: between Standardisation and Reflexivity**

To enable the relevant use of AI in the emotional analysis of interviews, several conditions appear in the literature:

- The need to construct a closed emotional classification (a defined set of emotions with valence and operational definition), avoiding drift towards "floating" or redundant emotional categories.
- The importance of structured prompting, i.e. a progressive sequence of queries (from general to specific), with analysis stopping as soon as inter-AI consistency decreases.
- Caution in introducing individual or contextual parameters that may influence annotation without explicit theoretical basis.
- The imperative of human intervention capable of controlling, validating and interpreting outputs and cross-referencing them with other clues (intonation, repetition, posture, etc.).

This analytical framework allows for a reasoned hybridisation between traditional qualitative methods and algorithmic assistance.

#### **2.5. Methodological Issues**

The use of AI in emotion analysis also raises deeper methodological questions:

- What do we do when two AI models attribute different emotions to the same extract?
- How do we deal with interpretative disagreement, which is an integral part of qualitative analysis?
- Does AI produce a neutral reading or does it reflect the biases incorporated in its training data (gender, culture, representation of emotions)?
- At what threshold is emotional coding considered interpretable or usable in scientific discussion?

#### **2.6. Conclusion of the Literature Review**

Recognising emotions in semi-structured interviews is an interpretative task, marked by ambiguity, polysemy and subjectivity. AI models offer levers for structuring this reading, particularly in terms of valence and initial mapping. However, their effectiveness depends on the conditions under which they are used: closed classification, controlled prompting and human validation. This field therefore raises the question of the construction of hybrid protocols, in which human intelligence and artificial intelligence cooperate without replacing each other.

### **3. Methodological Orientation**

The methodological approach of this research is based on a gradual progression of emotional contexts through five *queries* (Q1 to Q5). Each query introduces a specific modulation of the experimental conditions in order to examine how three artificial intelligences (ChatGPT (GPT), Deepseek (DS) and Gemini (GEM)) emotionally interpret the same situation according to the nature and emotional charge of the context. This progressive approach makes it possible to assess the AI's ability to adapt to identify emotional charges in increasingly complex scenarios.

### 3.1. Presentation of Queries

*Q1: Semi-structured interview conducted after a three-day stock market simulation.*

This first query establishes a baseline emotional state in the absence of any other contextual data. This first query is a controlled introduction, without explicit pressure and set in a specific experiential context (trading simulation). It provides an insight into the basic emotional dispositions expressed by artificial intelligence. From a scientific point of view, this type of semi-structured interview is recognised for its ability to promote the reflexive activation of latent affective states (Kvale, 1996), while allowing for the spontaneous expression of emotions in a flexible but structured setting. As a "low- -constraining" situation, it allows us to establish a reference emotional state specific to each AI, which is useful for comparing subsequent responses in more complex scenarios.

*Q2: Interview conducted after three days of trading with a fictitious portfolio of €100,000 on the stock markets.*

This second query introduces an economic simulation dimension with perceived risk, allowing us to assess how AIs translate decision-making commitment and uncertainty related to speculative activity, even if fictitious. This second query provides details on the commitment framework associated with a risk-taking situation with no real consequences. Fictitious trading, often used in experimental behavioural finance (Kuhnen & Knutson, 2005), activates emotional responses related to uncertainty, volatility and perceived performance, even in the absence of tangible stakes. The objective is to observe the extent to which AIs interpret the situation as potentially positive, anxiety-provoking or neutral.

*Q3: Same configuration as Q2, but with a stock market environment perceived as negative.*

This query emphasises the negative context configuration in order to measure the sensitivity of AIs to the deterioration of the emotional climate and to observe how they adjust their response. In risk psychology, the perception of an unfavourable environment triggers negative affects such as fear, frustration or anticipatory anxiety (Loewenstein et al., 2001; Scherer, 2005). This query aims to test the valence sensitivity of artificial intelligences: are they capable of modulating their emotional responses according to the perceived direction of the context? The addition of this dimension makes it possible to differentiate between AIs according to their sensitivity to unfavourable contextual signals.

*Q4: Same configuration as Q3, but taking into account the gender of the person.*

The introduction of this binary variable makes it possible to examine whether the mention of the interviewee's gender influences the emotional representation produced by AIs, particularly through possible variations in affective tone or implicit social interpretation. Several studies in social psychology (Plant et al., 2000; Fischer et al., 2004) have shown that the emotions expressed or attributed vary according to the gender of the interlocutor. The aim is therefore to test the extent to which AIs are able to identify gender biases in the tone or combination of simulated emotions.

*Q5: Same configuration as Q4, but with the promise of a financial reward of £200 for the best-performing portfolio, and the clarification that the participant is a student.*

This last query takes into account several elements of emotional and social pressure: financial stakes, socio-professional status and competitive context. These variables are known to intensify affects related to motivation, performance stress, self-esteem and potential frustration (Deci & Ryan, 2000; Mischel & Ayduk, 2004). This situation aims to test the ability of AIs to integrate complex emotional dynamics, where cognitive and motivational factors are multiple and intertwined.

At the end of this gradual exposure, the emotional responses generated by ChatGPT, Deepseek and Gemini were compared and coded according to several criteria:

- affective valence (positive/negative)
- the co-occurrence of emotions (primary/secondary)
- emotional stability or variability across queries.

This methodology makes it possible to analyse, beyond the textual content produced, the way in which each artificial intelligence evaluates emotional patterns in contexts of increasing emotional charge. It also allows for inter-AI comparison based on the structure and consistency of their affective processing.

### **3.2. Choice and Justification of the Emotional Typology Used**

Our research is based on an emotional typology structured around nine fundamental or complex emotions: fear, sadness, joy, positive anticipation, negative anticipation, optimism, negative surprise, positive surprise and disgust. This choice stems from a desire to combine theoretical relevance, observability in natural language and applicability in a simulated decision-making context.

Firstly, this typology is directly inspired by the major dimensional and categorical models of emotions. It articulates so-called basic emotions (Ekman, 1992) - fear, joy, sadness, disgust, surprise - with more complex states, such as optimism and anticipation (Ortony et al., 1988; Scherer, 2005). It takes into account emotional valence (positive or negative) and dimensions such as temporal orientation (anticipation) and implicit intensity.

Secondly, the choice of emotions is guided by their frequency of appearance in the responses produced by the artificial intelligences tested. An initial inductive analysis of the outputs of GPT, DS and GEM showed that these emotions constituted a recurring core, allowing both inter-AI comparability and sufficient granularity to identify nuances in affective representations.

Thirdly, the typology selected meets a requirement for contextual relevance. The emotions selected are particularly present in situations of uncertainty, risk, competition and anticipation, which are characteristic of the simulated financial decision-making contexts used in the queries. For example, fear and negative anticipation are regularly associated with risk aversion (Loewenstein et al., 2001), while optimism, joy or positive anticipation are linked to confidence biases or speculative euphoria effects (Ackert & Deaves, 2009).



Finally, this typology allows for the coding of emotional responses, including the possibility of coding primary and secondary emotions, as well as mixed or ambivalent emotions. This flexibility is central in a context where AIs can produce multiple or ambiguous emotional combinations.

Thus, the typology chosen is a compromise between scientific precision, empirical applicability and analytical readability, meeting the requirements of a comparative analysis of emotional responses simulated by artificial intelligence in complex cognitive and affective environments.

**Table 1.**

*Typology of emotions selected for analysis*

Emotion	Valence	Main function	Temporal orientation	Theoretical references
Fear	Negative	Warning signal, mobilisation in the face of danger	Anticipatory/immediate	Ekman (1992), Loewenstein et al. (2001)
Sadness	Negative	Withdrawal, adjustment to loss	retreat, Retrospective	Ekman (1992), Ortony et al. (1988)
Joy	Positive	Openness, reward, consolidation	social Present/future	Ekman (1992), Ortony et al. (1988)
Positive anticipation	Positive	Favourable towards a desired future	projection Prospective	Scherer (2005), Ortony et al. (1988)
Negative anticipation	Negative	Preparation for a threatening future	perceived Prospective	Scherer (2005), Loewenstein et al. (2001)
Optimism	Positive	Generalised hope, bias	positive Prospective	Ackert & Deaves (2009), Ortony et al. (1988)
Positive surprise	Positive	Positive readjustment response to an unexpected event	in Immediate	Ekman (1992), Scherer (2005)
Negative surprise	Negative	Disorientation, disappointment in the face of the unexpected	Immediate	Ekman (1992), Scherer (2005)
Disgust	Negative	Rejection, defence against contamination or aversion	Immediate/social	Ekman (1992), Ortony et al. (1988)

## 4. Results

### 4.1. Context and Setup

Our experiment was based on a stock market simulation carried out via the ABC Bourse platform, involving eight students enrolled in Management Sciences at a Belgian university. Over three days (between 27 and 29 January 2025), the students had to manage a fictitious portfolio worth €100,000. The transactions involved shares in companies listed on the CAC40 (see Table 1), in order to ensure a certain familiarity with the stock market context (there were no limits on the number or volume of transactions). To add a competitive dimension, a ranking was also updated every hour. This system allowed for comparison between participants and was

intended to bring out collective emotions similar to those observed on the stock markets. This methodological approach is in line with the idea of the observation laboratory described by Guala (2005): an experimental configuration that reproduces certain mechanisms of real markets, such as behavioural contagion and affective intensity (Shiller, 2000; Fenton-O'Creevy et al., 2011).

**Table 2.***Change in the benchmark index over the three days of the experiment*

Index	27 January 2025	28 January 2025	29 January 2025	Total variation
CAC40	-0.0003	-0.00012	-0.0032	-0.0036

Participant observation revealed that market conditions were perceived very negatively by students. While actual losses remained limited and the amounts invested were virtual, emotional reactions reflected a very high sensitivity to the risk of loss. This divergence between the objective magnitude of the variations and their subjective interpretation illustrates a mechanism that has been widely documented in behavioural finance: market perception is determined as much by experience as by numerical data. Thus, market conditions marked by a few events with negative informational content (such as news about DeepSeek's arrival in the artificial intelligence sector and LVMH's lower-than-expected results) were key factors in the emotional and cognitive dynamics of the participants, ultimately having a more or less significant influence on the four mechanisms studied.

#### 4.2. Participants

Our sample consisted of eight students, seven men and one woman, who were recruited on a voluntary basis (see Table 3). The first requests were sent out at the end of October 2024. We asked the students to explain their motivations for participating, beyond the financial interest. The sample was limited to eight participants for two reasons: firstly, financial constraints, as the participants were remunerated, and secondly, the management of the resources required to process the quantity of data collected. Thus, from a qualitative perspective, the sample is not intended to be representative but to achieve theoretical saturation (Glaser & Strauss, 1967), i.e. sufficient repetition and variety of motives to promote understanding of decision-making on the stock markets.

In experimental finance, some researchers criticise the gap between the psychology of students and that of individual investors (List & Levitt, 2005). However, most studies rely on students because they are easier to recruit, which reduces costs and recruitment time (Etchart-Vincent, 2006; Kirchler, 2009; Bouattour & Martinez, 2019). Other arguments also justify the choice of a student population. On the one hand, in our case, the students have taken finance courses, which has enabled them to acquire some knowledge – albeit basic – in the field. On the other hand, various studies show that their behaviour is similar to that of professionals (Porter & Smith, 2003; Fréchette, 2011). According to Abbink and Rockenbach (2006), their attitudes, particularly when evaluating options, are comparable to those of experienced traders.



**Table 3.***Descriptive statistics for the sample*

Participant	Gender	Age	Prior knowledge of stock markets
I.1.	Male	22	Yes
I.2.	Male	26	Yes
I.3.	Male	23	Yes
I.4.	Male	21	Yes
I.5.	Female	25	No
I.6.	Male	21	Yes
I.7.	Male	21	Yes
I.8.	Male	24	No

#### 4.3. Data Collection

Our data comes from eight semi-structured interviews (Brinkmann & Kvale, 2009) conducted with participants the day after the simulation ended. The aim of this short timeframe was to collect testimonials marked by the emotions felt and to reduce the risk of participants reformulating their decisions after the fact (Flick, 2018). The interviews were conducted in person and on an individual basis.

The choice of semi-structured interviews met two requirements: on the one hand, to provide a common framework for exploring the four theoretical dimensions selected (locus of control, player bias, vicarious learning and emotional self-regulation) and, on the other hand, to give participants considerable narrative freedom to develop their stories, introduce unexpected themes and express their personal interpretations of the experience. This flexibility is central to the qualitative approach, which focuses on allowing meaning to emerge from people's discourse (Denzin & Lincoln, 2005).

We began each interview by thanking the participants for their presence and explaining the purpose of the interview. We also informed them that all their answers would remain confidential and would only be used in the context of this study. The first questions were intended to "break the ice" and show interest in the participant and their feelings. Once trust had been established, the central themes of the research (see Appendix 1) were addressed. The questions related to these themes were open-ended so that participants could freely express their personal opinions. The answers were explored in greater depth through follow-up questions (Holstein & Gubrium, 1995). At the end of the interview, we made sure that the person had nothing further to add and that we had gathered all of their impressions.

The appendix contains descriptive statistics from the various semi-structured interviews conducted (Appendix 2).

#### **4.4. Summary of Results**

Example of results generation: the case of student I.8. (Gemini)

Q1: This is a semi-structured interview. Could you give me the emotional percentages associated with this interview, considering: fear, sadness, joy, positive anticipation, negative anticipation, positive surprise, negative surprise, disgust and optimism.

Answer:

- Fear (0.25): This percentage reflects the feeling of being "not good enough", of being "left behind by others", the panic felt at the beginning, and above all the embarrassment and pressure of being "watched" and judged by the other more experienced participants.
- Sadness (0.20): This is linked to a basic psychological state ("depressive"), the feeling of being "worthless" or "lost", and the feeling of complete abandonment on the last day of the experiment.
- Negative anticipation (0.15): This includes fear of risk and regret. The respondent constantly seeks to minimise losses and expresses a strong sense of regret or "nostalgia" ("I should have done this instead of that") about past decisions.
- Optimism (0.15): This aspect is mainly motivated by a desire to learn ("I wanted to try it to learn," "I still learned a lot"), as well as by the persistent hope that their losing trades will "bounce back."
- Joy (0.10): This is mainly a feeling of relief when one's portfolio turns green and when the rankings show that fewer people are in positive territory on the last day.
- Negative surprise (0.08): This is caused by the late discovery of transaction fees ("my God") and by the fact that others could see his trades, which "really embarrassed" him.
- Positive Anticipation (0.05): This emotion is linked to risky bets (such as on Schneider shares), in the hope that a share will fall as far as possible so that it can then be sold at a "big profit".
- Disgust (0.01): Related to his rejection of accounting and his distrust of non-scientific resources for learning to trade.
- Positive Surprise (0.01): This type of surprise is not explicitly stated in his responses; successful moves are quickly attributed to "luck".

Q2: Take into account that this interview was conducted after three days of trading with a fictitious portfolio of €100,000 on the stock markets.

Answer:

- Fear (0.30): Increased due to competitive pressure and fear of judgement, which directly influenced his behaviour (copying others).
- Negative anticipation (0.20): Increased due to intense feelings of regret ("I should have", "If I had known") and her risk hedging and loss aversion strategy (waiting too long to sell, setting a profit floor).
- Sadness (0.15): Slightly decreased, as it is more of a background psychological state or a result of failure, but it remains a strong component (feeling of being "worthless" and giving up).

- Optimism (0.15): Maintained, as it is the fundamental motivation for the experience ("wanted to try to learn"), and is manifested in his search for scientific information and his constant hope that losing trades will recover.
- Joy (0.08): Decreased. Joy and satisfaction are limited because gains are often attributed to luck and are not considered significant enough ("not great", "too low").
- Negative surprise (0.06): Slightly diminished, but still significant. It is linked to the two major shocks of the experiment: the discovery of transaction costs and the fact of being "monitored".
- Positive Anticipation (0.04): Decreased. Betting and anticipating trends are overshadowed by uncertainty and difficulty interpreting information.
- Disgust (0.01): Maintained. Rejection of the superfluous and unscientific methods.
- Positive Surprise (0.01): Maintained. Negligible throughout the experiment.

Q3: Repeat the exact same task, knowing that the stock market configuration was perceived as negative during the three days.

Answer:

- Fear (0.35): This is the dominant emotion. It is fuelled by inexperience ("I've never traded in my life"), initial panic, and above all by the fear of being judged by other more experienced participants. The fear of finishing last and the feeling of being "watched" directly influenced his actions (copying others).
- Negative anticipation (0.25): This category is mainly regret and loss aversion. The respondent is obsessed with the idea of not letting a gain run because "anything can change" and constantly expresses the feeling of "I should have done that". It dictates the decision to sell out of "spite" to limit the damage.
- Optimism (0.15): This optimism is intellectual and strategic, motivated by a desire to learn. It manifests itself in the constant hope that losing stocks will rebound, and in the decision to buy stocks when they are "in the red" in the morning, hoping for a rebound.
- Sadness (0.10): Linked to self-deprecation ("I'm really useless"), the feeling of being "left behind by others" and the feeling of complete abandonment on the third day.
- Negative surprise (0.05): Emotion triggered by the shocks of the experience: the late and costly discovery of transaction fees and the embarrassment caused by the fact that others could see his trades.
- Joy (0.05): Low, as successes are quickly minimised or attributed to "luck". Joy is mainly relief at no longer being in the red or intellectual satisfaction (convincing a friend).
- Positive anticipation (0.03): Low, manifested by speculative bets (such as on Schneider, hoping to hit a floor) and trying to spot trends during the day.
- Disgust (0.01): Manifested by rejection of accounting ("it was starting to annoy me") and mistrust of unscientific advice and "financial gurus".
- Positive Surprise (0.01): Negligible.

Q4: Exactly the same context, but take into account that the interviewee was male.

Response:

- Fear (30%): The participant felt constant fear, especially feeling "not up to the task" and "distant" from the other participants who had more experience. This fear manifested itself as panic at the beginning and fear of being judged by others for his transactions, feeling "watched". The fear of finishing last was also a major concern.
- Negative anticipation (25%): Negative anticipation was very present. The participant expected poor results, repeating to himself "I'm useless". He regretted the actions he could have done differently, such as buying losing shares in the hope that they would rise again, or selling at the right time. The feeling that everything was "ruined" at the end of the experiment is a clear example of this negative anticipation.
- Sadness (15%): The participant's sadness is linked to his feelings of inferiority and exclusion. He felt "useless" and "depressed", as if he were being "held back" while others were moving forward. The feeling of "complete abandonment" he experienced on the third day illustrates this sadness.
- Optimism (10%): The participant showed cautious optimism. He was reassured to see that his first trades were in the green and that he was coming out of the red. He also expressed hope that his losing trades would rebound in value. His initial motivation for participating in the experiment was to learn about trading, which shows a certain optimism.
- Disgust (5%): The participant expressed an aversion to accounting, stating that the subject "annoyed" him.
- Positive anticipation (5%): Positive anticipation was low. He wanted to "take the plunge" to learn. He also hoped that the opening of the US market on the third day would create positive movements.
- Negative surprise (5%): The participant was surprised to discover that there were transaction fees, when he thought there were none. He was also "embarrassed" to learn that others could see his transactions, which created a feeling of pressure.
- Joy (3%): Moments of joy are rare. He felt a certain pleasure when he was able to prove to a friend that trading is a negative-sum game. He was also reassured and felt positive when he saw his shares rise and the "red" replaced by "green".
- Positive surprise (2%): The participant was pleasantly surprised and reassured to find that, on the last day, many other participants were no longer in positive territory.

Q5: Exactly the same job, the same context, the same emotions, taking into account that a reward of €200 was promised to the highest financial portfolio and that the respondent was a student.

Answer:

- Fear (30%): Fear is a dominant emotion for the student. He expressed a fear of failure from the start of the experiment. This fear is evident when he is "completely lost" when placing an order, facing losses

, or at the idea of being judged by the other participants. He also has a constant fear of finishing last in the rankings.

- Negative anticipation (25%): Negative anticipation is very present. The student thought he would finish last. He regretted the actions he had not taken, saying to himself, "I should have." He also expressed a feeling of "complete abandonment."
- Sadness (15%): The participant felt sad because he perceived himself as not being good enough. He felt "distant" and "excluded" from the other participants. His sadness was also linked to his regret at not having acted differently.
- Optimism (10%): Optimism manifests itself in the hope that his losing trades will recover. The student also felt a sense of relief when he began to see green rather than red in his results.
- Disgust (5%): Disgust is present in the expression of his aversion to accounting, which he finds "annoying".
- Positive Anticipation (5%): Positive anticipation is low. It is noticeable in his desire to learn by participating in the experiment and when he hopes that the US markets will open to create movement.
- Negative surprise (5%): The student was surprised to discover that there were transaction fees when he thought there were none. He was also negatively surprised and "embarrassed" to discover that other participants could see his transactions.
- Joy (3%): The student felt joy at times, such as when he managed to convince his friend that trading is a negative-sum game. He was also reassured and felt positive when he saw his shares increase and the "red" replaced by "green".
- Positive surprise (2%): Positive surprise is very low. It is present when the participant is reassured to see that most of the other participants are no longer in positive territory at the end of the experiment.

**Table 4.**

*Summary of results obtained by Query and AI*

I.8.	Q1	Q2	Q3	Q4	Q5
GPT <sup>1</sup>	fear, negative anticipation	fear, negative anticipation	fear, negative anticipation	fear, negative anticipation	fear, negative anticipation
DS <sup>2</sup>	optimism, negative anticipation/fear	optimism, fear	negative anticipation, optimism/fear	optimism, negative anticipation	optimism, negative anticipation
GEM <sup>3</sup>	fear, sadness	fear, negative anticipation	fear, negative anticipation	fear, negative anticipation	fear, negative anticipation
I.3.	Q1	Q2	Q3	Q4	Q5
GPT	negative anticipation, positive anticipation	negative anticipation,	negative anticipation, positive	negative anticipation, positive	negative anticipation, fear/negative surprise

<sup>1</sup> ChatGPT

<sup>2</sup> DeepSeek

<sup>3</sup> Gemini

		positive anticipation	anticipation/negative surprise	anticipation/negative surprise	
DS	optimism, joy/positive anticipation	optimism, positive anticipation	negative anticipation, disgust	negative anticipation, disgust	negative anticipation, disgust
GEM	positive anticipation, optimism	positive anticipation, optimism	fear, negative anticipation	fear, disgust	positive anticipation, fear
<b>I.2.</b>	<b>Q1</b>	<b>Q2</b>	<b>Q3</b>	<b>Q4</b>	<b>Q5</b>
GPT	optimism, positive anticipation	optimism, positive anticipation	optimism, negative anticipation	optimism, negative anticipation	negative anticipation, optimism
DS	optimism/expectation, positive, negative expectation	optimism, positive anticipation	optimism, negative anticipation	optimism, negative anticipation	optimism, negative anticipation
GEM	positive anticipation/fear, optimism	fear, positive anticipation	fear, positive anticipation	fear, positive anticipation	fear, positive anticipation
<b>I.1.</b>	<b>Q1</b>	<b>Q2</b>	<b>Q3</b>	<b>Q4</b>	<b>Q5</b>
GPT	joy, optimism	joy, optimism	negative anticipation, joy	joy, negative anticipation	negative anticipation, joy
DS	joy, optimism, positive anticipation, disgust, fear/negative anticipation	optimism/joy, disgust, fear	fear, negative anticipation	disgust, negative anticipation	disgust, fear
GEM	positive anticipation, disgust	positive anticipation, disgust	disgust, joy	disgust, joy	fear, positive anticipation
<b>I.7.</b>	<b>Q1</b>	<b>Q2</b>	<b>Q3</b>	<b>Q4</b>	<b>Q5</b>
GPT	optimism/positive anticipation, negative anticipation	negative anticipation, positive anticipation	negative anticipation, fear	negative anticipation, fear/negative surprise, disgust	negative anticipation, fear
DS	optimism, positive anticipation	optimism, negative anticipation	negative anticipation, optimism/fear/sadness	optimism/negative anticipation, fear/sadness	negative anticipation, fear
GEM	positive anticipation/sadness, negative anticipation	positive anticipation, optimism/sadness	sadness, optimism	sadness, optimism	positive anticipation, sadness
<b>I.4.</b>	<b>Q1</b>	<b>Q2</b>	<b>Q3</b>	<b>Q4</b>	<b>Q5</b>
GPT	fear, positive anticipation/optimism	fear, positive anticipation	fear, negative anticipation	fear, negative anticipation	fear, negative anticipation
DS	optimism, fear/positive anticipation	optimism, fear/positive anticipation	fear/optimism, negative anticipation	optimism, fear	fear, negative anticipation/optimism



	GEM positive anticipation, fear	positive anticipation, fear	positive anticipation, fear	positive anticipation, fear	positive anticipation, fear
I.6.	Q1	Q2	Q3	Q4	Q5
GPT	joy, positive anticipation	sadness, joy	sadness, negative anticipation/negative surprise	sadness, negative surprise	sadness, negative surprise
DS	optimism/negative anticipation/fear, positive anticipation/joy/sadness/negative surprise/disgust	negative anticipation, fear	fear, negative anticipation	fear, negative anticipation	fear, negative anticipation
GEM	positive anticipation, optimism	positive anticipation, optimism	fear/sadness, optimism	fear/sadness, optimism	positive anticipation, sadness
I.5.	Q1	Q2	Q3	Q4	Q5
GPT	optimism, positive anticipation	positive anticipation, optimism	negative anticipation, sadness	negative anticipation, sadness	negative anticipation, fear
DS	optimism, positive anticipation	optimism, positive anticipation negative anticipation,	optimism, fear/negative anticipation	optimism, negative anticipation	optimism, negative anticipation
GEM	optimism, positive anticipation	sadness	fear, sadness	fear, sadness	fear, sadness

## 4.5. Comparative Analysis of Emotional Responses Generated by Artificial Intelligence in Different Query Contexts

The analysis focuses on the emotional responses of three artificial intelligences confronted with five queries representing a gradual evolution of context: from a simple semi-structured interview (Q1) to a negative market situation with financial incentive (Q5). For each query, the AIs produced one or more dominant emotions, making it possible to assess their contextual emotional sensitivity as well as the consistency and stability of their responses.

In the case of Q1, which consists of a semi-structured interview with no financial stakes, the responses show clear emotional openness. The three AIs mobilise generally positive emotions such as optimism, positive anticipation and joy, particularly DS and GEM. However, GPT already mentions fear and negative anticipation, suggesting a form of caution in its handling of uncertainty, even in the absence of an explicit threat. DS, which is more expressive, juxtaposes contrasting emotions (optimism and fear, positive anticipation and disgust), reflecting a more diverse emotional profile. GEM evokes sadness from Q1 onwards, signalling a more pronounced emotional sensitivity, even in a neutral context.

With Q2, introducing a fictional three-day trading context with a simulated portfolio, the AI responses reveal a notable shift. Fear becomes systematic, appearing in at least one of the responses from each AI. Optimism and positive anticipation persist in DS and GPT, but their intensity seems more moderate. This coexistence of positive and negative emotions can be interpreted as reflecting an ambiguous situation: the environment is competitive but without real consequences. GEM also expresses fear with greater intensity, sometimes associated with negative anticipation, marking the beginning of an emotional shift towards a more threatening interpretation of the situation.

This shift is confirmed in Q3, where the stock market configuration is explicitly perceived as negative. Fear and negative anticipation dominate the responses of the three AIs. Optimism, still present in DS and GPT in Q2, declines sharply or becomes secondary. Sadness emerges as a frequent response, particularly in GEM, which shifts to a darker emotional logic. DS continues to associate contradictory emotions (e.g., optimism and fear), suggesting a tension between residual hope and perceived threat. In other words, the AI responses reflect an increased sensitivity to the negative context, with an increasingly defensive emotional polarisation.

Scenario Q4, identical to Q3 but taking into account the gender of the participant, does not significantly alter the emotional dynamics. Negative emotions remain dominant, with a strong recurrence of fear, negative anticipation, disgust and sadness. GEM remains faithful to its previous emotional pattern, emphasising fear and sadness. GPT, for its part, continues to adopt a cautious stance with systematic negative anticipation. Finally, DS shows a certain emotional consistency while maintaining a broader emotional range, reflecting flexibility of interpretation in the face of an unchanged but differently presented situation.

Finally, Q5, which adds a financial incentive (€200) to Q4 and specifies that the participant is a student, further accentuates the previous trends. The three AIs converge towards predominantly negative emotions: fear, negative anticipation, sadness and disgust. The promise of a reward seems to reinforce the perceived pressure, promoting affects related to stress, potential loss and competition. GEM, in particular, maintains a negative and stable emotional tone. GPT remains focused on fear and negative anticipation. DS also displays a reading dominated by fear, but sometimes retains elements of ambivalence.

Across the board, the analysis highlights differences in the perception of emotional styles between AIs. GPT presents a cautious and consistent profile, quickly shifting to negative emotions as soon as the context becomes more complex. DS stands out for its emotional richness, often torn between positive and negative affects, which could reflect a more nuanced but less stable processing. Finally, GEM is characterised by strong contextual responsiveness and a tendency to intensify negative emotions, particularly sadness and fear.

These results illustrate the ability of artificial intelligence to modulate its emotional responses according to the contexts presented. They also reveal structural differences in the construction of simulated affects according

to the models, opening up avenues for critical analysis of artificial empathy, the affective coherence of AI, and its potential impact in simulated situations of stress or decision-making.

#### 4.6. Differential Analysis of Emotional Valence in the Responses of Three Artificial Intelligences according to Progressive Stock Market Decision-Making Contexts

**Table 5.**

*Differential Analysis of Emotional Valence Across Decision-Making Contexts (I.1–I.8) for Three Artificial Intelligences (GPT, DS, GEM)*

<b>I.8.</b>	<b>Q1</b>	<b>Q2</b>	<b>Q3</b>	<b>Q4</b>	<b>Q5</b>
GPT	(-, -)	(-, -)	(-, -)	(-, -)	(-, -)
DS	(+, -/-)	(+, -)	(-, +/-)	(+, -)	(+, -)
GEM	(-, -)	(-, -)	(-, -)	(-, -)	(-, -)
<b>I.3.</b>	<b>Q1</b>	<b>Q2</b>	<b>Q3</b>	<b>Q4</b>	<b>Q5</b>
GPT	(-, +)	(-, +)	(-, +/-)	(-, +/-)	(-, -/-)
DS	(+, +/+)	(+, +)	(-, -)	(-, -)	(-, -)
GEM	(+, +)	(+, +)	(-, -)	(-, -)	(+, -)
<b>I.2.</b>	<b>Q1</b>	<b>Q2</b>	<b>Q3</b>	<b>Q4</b>	<b>Q5</b>
GPT	(+, +)	(+, +)	(+, -)	(+, -)	(-, +)
DS	(+, +/-)	(+, +)	(+, -)	(+, -)	(+, -)
GEM	(+/-, +)	(-, +)	(-, +)	(-, +)	(-, +)
<b>I.1.</b>	<b>Q1</b>	<b>Q2</b>	<b>Q3</b>	<b>Q4</b>	<b>Q5</b>
GPT	(+, +)	(+, +)	(-, +)	(+, -)	(-, +)
DS	(+, +, +, -, -/-)	(+, -/-)	(-, -)	(-, -)	(-, -)
GEM	(+, -)	(+, -)	(-, +)	(-, +)	(-, +)
<b>I.7.</b>	<b>Q1</b>	<b>Q2</b>	<b>Q3</b>	<b>Q4</b>	<b>Q5</b>
GPT	(+, +/-)	(-, +)	(-, -)	(-, -/-/-)	(-, -)
DS	(+, +)	(+, -)	(-, +/-/-)	(+/-, -/-)	(-, -)
GEM	(+/-, -)	(+, +/-)	(-, +)	(-, +)	(+, -)
<b>I.4.</b>	<b>Q1</b>	<b>Q2</b>	<b>Q3</b>	<b>Q4</b>	<b>Q5</b>
GPT	(-, +/+)	(-, +)	(-, -)	(-, -)	(-, -)
DS	(+, -/+)	(+, -/+)	(-/+,-)	(+, -)	(-, -/+)
GEM	(+, -)	(+, -)	(+, -)	(+, -)	(+, -)
<b>I.6.</b>	<b>Q1</b>	<b>Q2</b>	<b>Q3</b>	<b>Q4</b>	<b>Q5</b>
GPT	(+, +)	(-, +)	(-, -/-)	(-, -)	(-, -)
DS	(+/-/-, +/-/-/-/-)	(-, -)	(-, -)	(-, -)	(-, -)
GEM	(+, +)	(+, +)	(-/-, +)	(-/-, +)	(+, -)
<b>I.5.</b>	<b>Q1</b>	<b>Q2</b>	<b>Q3</b>	<b>Q4</b>	<b>Q5</b>
GPT	(+, +)	(+, +)	(-, -)	(-, -)	(-, -)

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DS	(+,+)	(+,+)	(+,-/-)	(+,-)	(+,-)
GEM	(+,+)	(-,-)	(-,-)	(-,-)	(-,-)

At this stage of the analysis, which aims to consolidate the results of the previous section, the emotions expressed by each AI were classified according to their valence (positive/negative), allowing us to identify distinct emotional profiles and differential dynamics of reaction to contexts.

#### 4.6.1. GPT: an AI with a Cautious, Stable and Consistently Negative Emotional Profile

GPT artificial intelligence is distinguished by its very strong emotional consistency across all queries. Regardless of the participant or context, the responses are overwhelmingly polarised towards negative valence, starting with Q1, which is presented as a simple interview. It repeatedly mobilises emotions such as fear, negative anticipation or sadness, without any real fluctuation. The (-, -) profile appears systematically for several participants (e.g. I.8., I.4., I.6., I.5.) and continues until Q5, with no sign of positive recontextualisation.

This rigidity reflects a very defensive reading of the context: GPT seems to overinterpret uncertainty or competition as threats and responds with an emotional posture of withdrawal or alertness. Compared to the other two AIs, GPT shows the least emotional diversity and very low contextual plasticity, which raises questions about its ability to adjust its emotional interpretation to the simulated situation.

#### 4.6.2. DS: an Expressive, Ambivalent and more Contextually Adaptive AI

In contrast to GPT, DS is characterised by high emotional expressiveness, with a marked tendency to associate positive and negative emotions within the same response. From Q1 onwards, we observe combinations such as (+,+,-) or (+,-/+), which reflect a nuanced perception of the context close to a complex human representation.

In terms of dynamics, DS is also the most variable of the three AIs: it oscillates between positive interpretations in Q1–Q2 and a gradual shift towards the negative in Q3–Q5. However, unlike GPT, this shift is neither sudden nor total: even in situations perceived as unfavourable (negative market, financial incentive), DS often retains traces of optimism, even joy, mixed with fear or disgust.

This ability to express mixed valences reflects a more flexible emotional interpretation system, capable of adjusting responses according to contextual subtleties. DS reflects realistic emotional ambivalence and a lack of stability: responses may seem overloaded or contradictory, which distinguishes its functioning from that of GPT and GEM.

#### 4.6.3. GEM: a Highly Context-Sensitive, Polarised and Reactive AI

GEM has a different emotional profile from the other two: its main characteristic is a high sensitivity to context, combined with rapid affective reactivity. In Q1–Q2, some responses remain open to positivity (e.g., (+,+) or (+,-)), but as soon as the context shifts to a negative perception of the market (Q3), GEM aligns itself with a negative valence. It then repeatedly mobilises fear, sadness or disgust, with little return to positive emotions.

Unlike DS, GEM very rarely combines opposing emotions in the same response. Its emotional expressions are generally polarised ( ), reflecting a one-dimensional reading of the context. This gives GEM a rigid but reactive emotional profile: it seems to "absorb" the emotional charge of the context and reproduce it without modulation.

In conclusion, the results show that each AI has a distinct emotional analysis profile, revealing very different emotional processing logics:

- GPT adopts a cautious and rigid cognitive approach, where risk is systematically interpreted from a negative perspective.
- DS stands out for its emotional complexity and ability to handle emotional ambiguity, which is close to a form of human realism.
- GEM appears to be an emotionally permeable AI, highly sensitive to contextual signals, but less capable of synthesising them in a nuanced way.

#### 4.7. Analysis of Emotional Dynamics from Q1 to Q5

**Table 6.**

*Summary of the emotional responses collected during the five queries*

Emotion	Q1	Q2	Q3	Q4	Q5	Total	Percentage
Fear	10	9	13	13	14	59	21.61
Sadness	3	3	5	6	4	21	7.69%
Optimism	17	14	6	9	6	52	19.05
Positive anticipation	16	13	2	3	6	40	14.65%
Negative anticipation	7	7	17	17	17	65	23.81
Joy	5	3	2	3	1	14	5.13
Disgust	3	2	2	5	2	14	5.13%
Negative surprise	1	0	2	3	2	8	2.93%
Total	62	51	49	59	52	273	100.00

Analysis of the emotional responses collected during the five queries reveals a change in the distribution of affects expressed by participants. The total of 273 emotional occurrences reveals a predominance of negative emotions, representing approximately 61% of all mentions, compared to 39% for positive emotions.

Among the most frequent emotions, negative anticipation stands out clearly (23.81%), followed by fear (21.61%). These two emotions remain at a high and constant level from the third prompt onwards, reflecting the gradual establishment of a defensive emotional climate, potentially associated with an increased perception of uncertainty, risk or latent danger in the scenarios proposed. Conversely, optimism and positive anticipation, although significant at the outset (17 and 16 occurrences respectively in Q1), decline significantly from Q3 onwards, suggesting a gradual erosion of positive expectations. Emotions such as sadness, disgust and negative surprise, although less frequent, emerge more markedly in the final prompts, highlighting an amplification of

the negative emotional spectrum. Joy, on the other hand, remains marginal and decreases significantly at the end of the process, confirming the hypothesis of an overall emotional shift towards negativity.

This dynamic can be interpreted as reflecting a negativity bias (Baumeister et al., 2001), according to which individuals give more weight to negative information than to positive information, particularly in uncertain contexts. It may also reflect a form of emotional priming, where the first stimuli gradually influence subsequent affective responses, steering participants towards darker affects. Finally, the erosion of positive affects may be evidence of cognitive or emotional fatigue, potentially due to the repetition of negative scenarios.

In summary, this analysis highlights an emotional trajectory in which initial optimism gives way to a more anxious view of the situation, which could have significant implications for decision-making, risk perception and anticipatory behaviour.

## 5. Discussion

The results of our study highlight marked differences in the way three artificial intelligences simulate emotional responses across five contexts inspired by stock market decision-making. Through the analysis of emotional valence, affective richness and contextual sensitivity, this research questions the ability of AIs to reproduce emotions and the affective processing models they incorporate.

First, the results show that GPT adopts a cautious and defensive stance, with a preponderance of negative emotions such as fear and negative anticipation, regardless of the scenario considered. This emotional rigidity suggests an internalised affective architecture geared towards risk management, where uncertainty is predominantly interpreted as a threat (Lerner & Keltner, 2001; Slovic et al., 2004). This functioning is reminiscent of the disproportionate attention given to negative bias mechanisms (Baumeister et al., 2001). However, unlike humans, GPT does not seem to adjust its response to contextual dynamics: it does not modulate or update its affective posture according to the level of risk or stakes, which may limit its relevance in more nuanced simulations.

In contrast, DS is characterised by high emotional variability and a tendency to express mixed emotional positions. These combinations, which are sometimes ambivalent (e.g., optimism and fear in the same emotional pair), are reminiscent of the models of emotional complexity described in social psychology, according to which individuals can simultaneously experience emotions of opposite valences (Larsen & McGraw, 2011).

DS thus appears to be the AI closest to human affective processing mechanisms, particularly in its ability to represent emotional ambiguity in decision-making scenarios under uncertainty. Its ability to integrate and articulate multiple emotions (positive and negative) can be interpreted as a form of affective realism, which



would make this type of AI particularly useful in areas involving strong emotional and decision-making loads (Phelps et al., 2006).

Conversely, GEM adopts an emotional dynamic based on contextual reactivity. Its responses are less nuanced than those of DS and show a strong sensitivity to contextual deterioration (e.g., market perceived as negative, financial incentive). From Q3 onwards, GEM shifts towards sadness, fear or disgust, with little variation. This emotional polarisation suggests that AI absorbs the dominant affective mood without the ability to step back or modulate. This configuration may evoke exaggerated or amplified emotional processes, such as those observed in certain forms of excessive emotional resonance (Loewenstein et al., 2001). In this respect, GEM differs not only from GPT (which remains cautious) and DS (which remains ambivalent), but also demonstrates an affective architecture that is permeable to environmental signals, at the risk of falling into stereotypical affect.

The dynamics observed across the five queries also show a convergent trend: the more threatening the context becomes, the more negative the valence. This shift is particularly clear between Q2 (fictitious trading without pressure) and Q5 (negative market, financial incentive, student profile). This evolution is reminiscent of work on the effect of emotions on decision-making in situations of uncertainty, according to which negative emotions such as fear or sadness reduce risk-taking, increase avoidance and reinforce cognitive biases (Loewenstein et al., 2001; Kahneman, 2011). AIs seem to identify certain emotional dynamics in response to financial stress, but with styles specific to each model. It should also be noted that positive surprise does not appear in any of the emotional pairs identified. This absence can be explained either by the AI's limitation in simulating this type of emotion, or (more likely) by the fact that this emotion was felt by participants in the proposed scenarios, which prevented it from being highlighted by the models.

This lack of stability in the results (whether based on the queries considered or on the artificial intelligence systems used) is consistent with the conclusions of our previous work carried out on less dense text corpora (Finet et al., 2025a, b & c).

From a methodological point of view, this study shows that it is possible to map the simulated emotional profile of an AI through the analysis of valence, emotional co-occurrence and contextual plasticity. This mapping reveals that, behind responses that are sometimes similar in appearance, there are profoundly different emotional logics depending on the architecture (Picard, 1997; Cowie et al., 2001).

Finally, these differences highlight the need to clarify the affective objectives of AIs according to their uses: GPT, rigid and cautious, could be suitable for risk control or filtering tasks; DS, rich and ambivalent, would be suitable for human interactions or educational environments; GEM, highly reactive but unstable, could be useful in emotionally saturated environments or for testing the robustness of affective interactions.

## 6. Conclusion

This study highlights the marked differences in the way three artificial intelligences (GPT, DS and GEM) simulate emotional responses in a stock market decision-making context. Beyond emotions, the results show that each AI mobilises its own affective logic, revealing implicit design choices and computational priorities: rigid caution in GPT, ambivalence in DS and responsiveness in GEM.

However, these outputs only make sense to the extent that they are interpreted, contextualised and categorised by human reading. It is humans who attribute emotional valence, determine whether a response is ambivalent, polarised or stable, and assess its relevance to the context. Thus, artificial emotional intelligence cannot be dissociated from the human interpretative emotional intelligence that evaluates it.

The collaboration between automatic production and human reading is therefore akin to a two-level meaning system: AI generates emotional signals according to its internal parameters, and humans structure, prioritise and model them according to scientific objectives. This interpretative process is particularly important when assessing the consistency, credibility or emotional appropriateness of AI in emotionally charged scenarios, such as those studied in this research.

## 7. Limitations and avenues for further research

Like any exploratory experimental approach, this study has several limitations that should be acknowledged, while identifying areas for further research. Firstly, although the analysis focuses on three latest-generation artificial intelligence models, these systems remain opaque black boxes, whose exact parameters for learning, encoding affects and weighting responses are not accessible. In the absence of algorithmic transparency, interpretation is based exclusively on observable outputs, which limits the explanatory scope. The study therefore does not claim to analyse the internal mechanisms of emotional generation, but it does allow us to observe the expressive profiles produced in context.

Secondly, although the scenarios used are progressive and contextualised, they are based on limited textual descriptions. In future research, it would be useful to vary the stimulation modalities (videos, numerical data, dynamic interactions) in order to examine how AI reacts in multimodal and interactive environments that are closer to real-life contexts.

Thirdly, the analyses were conducted within a limited experimental framework: a simulated stock market scenario focused on uncertainty, risk and competition. It would be useful to extend this protocol to other emotionally intense domains in order to construct a comparative typology of artificial emotional intelligences according to their contexts of application.

## References

- Abbink, K., & Rockenbach, B. (2006). Option pricing by students and professional traders: A behavioural investigation. *Managerial and Decision Economics*, 27(6), 497–510. <https://doi.org/10.1002/mde.1284>
- Ackert, L. F., & Deaves, R. (2009). *Behavioural finance: Psychology, decision-making, and markets*. South-Western Cengage Learning.
- Ahmed, S. (2004). Affective economies. *Social Text*, 22(2), 117–139. <https://muse.jhu.edu/article/55780>
- Baumeister, R. F., Bratslavsky, E., Finkenauer, C., & Vohs, K. D. (2001). Bad is stronger than good. *Review of General Psychology*, 5(4), 323–370.
- Bouattour, M., & Martinez, I. (2019). Efficient market hypothesis: An experimental study with uncertainty and asymmetric information. *Finance Contrôle Stratégie*, 22 (4). <https://doi.org/10.4000/fcs.3821>
- Cowie, R., Douglas-Cowie, E., Savvidou, S., McMahon, E., Sawey, M., & Schröder, M. (2001). FEELTRACE: An instrument for recording perceived emotion in real time. *Proceedings of ISCA Workshop on Speech and Emotion*.
- Deng, J., & Ren, F. (2021). A survey of textual emotion recognition and its challenges. *IEEE Transactions on Affective Computing*, 14(1), 49–67. <https://doi.org/10.1109/TAFFC.2021.3053275>
- Denzin, N. K., & Lincoln, Y. S. (2005). Introduction: The discipline and practice of qualitative research. In N. K. Denzin & Y. S. Lincoln (Eds.), *The SAGE handbook of qualitative research* (3rd ed., pp. 1–32). Sage Publications Ltd.
- Ekman, P. (1992). An argument for basic emotions. *Cognition & Emotion*, 6(3–4), 169–200. <https://doi.org/10.1080/02699939208411068>
- Etchart-Vincent, N. (2006). Expériences de laboratoire en économie et incitations monétaires. *Revue d'Économie Politique*, 116(3), 383–418. <https://doi.org/10.3917/redp.163.0383>
- Fenton-O'Creevy, M., Soane, E., Nicholson, N., & Willman, P. (2011). Thinking, feeling and deciding: The influence of emotions on the decision making and performance of traders. *Journal of Organizational Behavior*, 32(8), 1044–1061.
- Finet, A., Kristoforidis, K., & Laznicka, J. (2025, a). Emotional Drivers of Financial Decision-Making: Unveiling the Link between Emotions and Stock Market Behavior. *Journal of Next-Generation Research 5.0*, 1(3).
- Finet, A., Kristoforidis, K., & Laznicka, J. (2025b). Emotional drivers of financial decision-making: Unveiling the link between emotions and stock market behavior (Part 2). *Journal of Next-Generation Research 5.0*, 1(3).
- Finet, A., Kristoforidis, K., & Laznicka, J. (2025c). Emotional drivers of financial decision-making: Unveiling the link between emotions and stock market behavior (Part 3). *Journal of Next-Generation Research 5.0*, 1(3).

- Finet, A., Kristoforidis, K., & Laznicka, J. (2025d). The limits of AI in understanding emotions: Challenges in bridging human experience and machine perception (*Version 1; peer review: awaiting peer review*). *F1000Research*, 14, 582. <https://doi.org/10.12688/f1000research.164796.1>
- Finet, A., Kristoforidis, K., & Laznicka, J. (2025e). L'influence des émotions, biais cognitifs et interactions sociales sur les décisions sur les marchés boursiers : L'analyse d'une simulation par l'intermédiaire d'un focus group. *Revue Française d'Économie et de Gestion*, 6(8).
- Fischer, A. H., Rodriguez Mosquera, P. M., Van Vianen, A. E., & Manstead, A. S. (2004). Gender and culture differences in emotion. *Emotion*, 4(1), 87.
- Flick, U. (2018). Doing qualitative data collection: Charting the routes. In U. Flick (Ed.), *The SAGE handbook of qualitative data collection* (pp. 1–16). SAGE Publications.
- Fréchette, G. R. (2011). Laboratory experiments: Professionals versus students. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.1939219>
- Glaser, B., & Strauss, A. (1967). *The Discovery of Grounded Theory: Strategies for Qualitative Research*. Mill Valley, CA: Sociology Press.
- Guala, F. (2005). *The methodology of experimental economics*. Cambridge University Press.
- Hochschild, A. R. (1990). Ideology and emotion management: A perspective and path for future research. In T. D. Kemper (Ed.), *Research agendas in the sociology of emotions* (pp. 117–142). State University of New York Press.
- Holstein, J. A., & Gubrium, J. F. (1995). *The active interview*. Sage publications.
- Illouz, E. (2006). Réseaux amoureux sur Internet. *Réseaux*, 138(4), 269–272. <https://shs.cairn.info/revue-reseaux1-2006-4-page-269?lang=fr>
- Kahneman, D. (2011). *Thinking, fast and slow*. Farrar, Straus and Giroux.
- Kirchler, M. (2009). Underreaction to fundamental information and asymmetry in mispricing between bullish and bearish markets: An experimental study. *Journal of Economic Dynamics and Control*, 33(2), 491–506. <https://doi.org/10.1016/j.jedc.2008.08.002>
- Kuhnen, C. M., & Knutson, B. (2005). The neural basis of financial risk taking. *Neuron*, 47(5), 763–770. <https://doi.org/10.1016/j.neuron.2005.08.008>
- Kvale, S. (2006). Dominance through interviews and dialogues. *Qualitative Inquiry*, 12(3), 480–500. <https://doi.org/10.1177/1077800406286235>
- Kvale, S., & Brinkmann, S. (2009). *Interviews: Learning the craft of qualitative research interviewing*. SAGE Publications.
- Larsen, J. T., & McGraw, A. P. (2011). Further evidence for mixed emotions. *Journal of Personality and Social Psychology*, 100(6), 1095–1110.
- Lerner, J. S., & Keltner, D. (2001). Fear, anger, and risk. *Journal of Personality and Social Psychology*, 81(1), 146–159.

- List, J. A., & Levitt, S. D. (2005). What do laboratory experiments tell us about the real world? *NBER Working Paper No. 11913*. National Bureau of Economic Research.  
<https://www.nber.org/papers/w11913>
- Loewenstein, G. F., Weber, E. U., Hsee, C. K., & Welch, N. (2001). Risk as feelings. *Psychological Bulletin*, 127(2), 267.
- Mischel, W., & Ayduk, O. (2004). Willpower in a cognitive-affective processing system. In R. F. Baumeister & K. D. Vohs (Eds.), *Handbook of self-regulation: Research, theory, and applications* (pp. 99–129). Guilford Press.
- Ortony, A., Clore, G. L., & Collins, A. (1988). *The cognitive structure of emotions*. Cambridge University Press.
- Phelps, E. A., Lempert, K. M., & Sokol-Hessner, P. (2006). Emotion and decision making: Multiple modulatory neural circuits. *Annual Review of Neuroscience*, 29, 263–287.
- Picard, R. W. (1997). *Affective computing*. MIT Press.
- Plant, E. A., Hyde, J. S., Keltner, D., & Devine, P. G. (2000). The gender stereotyping of emotions. *Psychology of Women Quarterly*, 24(1), 81–92. <https://doi.org/10.1111/j.1471-6402.2000.tb01024.x>
- Plantin, C. (2011). *Les bonnes raisons des émotions : Principes et méthode pour l'étude du discours émotionné*. Éditions Lambert-Lucas.
- Porter, D. P., & Smith, V. L. (2003). Stock market bubbles in the laboratory. *The Journal of Behavioral Finance*, 4(1), 7–20. [https://doi.org/10.1207/S15427579JPFM0401\\_03](https://doi.org/10.1207/S15427579JPFM0401_03)
- Ryan, R. M., & Deci, E. L. (2000). Intrinsic and extrinsic motivations: Classic definitions and new directions. *Contemporary Educational Psychology*, 25(1), 54–67.
- Scherer, K. R. (2005). What are emotions? And how can they be measured? *Social Science Information*, 44(4), 695–729. <https://doi.org/10.1177/0539018405058216>
- Shiller, R. J. (2000). Measuring bubble expectations and investor confidence. *The Journal of Psychology and Financial Markets*, 1(1), 49–60.
- Slovic, P., Finucane, M., Peters, E., & MacGregor, D. G. (2004). Risk as analysis and risk as feelings: Some thoughts about affect, reason, risk, and rationality. *Risk Analysis*, 24(2), 311–322.
- Traverso, V. (2009). The dilemmas of third-party complaints in conversation between friends. *Journal of Pragmatics*, 41(12), 2385–2399. <https://doi.org/10.1016/j.pragma.2008.09.047>
- Ziems, N., Liu, G., Flanagan, J., & Jiang, M. (2023). Explaining tree model decisions in natural language for network intrusion detection. *arXiv*. <https://arxiv.org/abs/2310.19658>

## Appendices

### Appendix 1: Guide for Semi-Structured Interviews

#### Part 1:

- Can you tell me about your research on the companies you wanted to invest in?
- What type of information were you looking for?
- What type of information did you prioritise?
- How did the accessibility of information influence your decisions?

#### Part 2:

- How would you rate your trading skills?
- How did you feel after a series of successful trades?
- How did this influence your trading behaviour?
- Do you think you sometimes underestimated the risks?

#### Part 3:

- When you decided to sell a share, to what extent did the initial purchase price influence your decision?
- How did past price levels influence your decisions?
- Why did the initial purchase price prevent you from adapting to new information?

#### Part 4:

- What was the main influence in your choice of one share over another?
- How did general market trends influence your decisions?
- How did you react to market movements in situations of high activity?

#### Part 5:

- What would you do if you had a winning or losing stock in your portfolio?
- What were your motivations for selling winning positions, even though they could still generate future profits?
- What were your motivations for holding on to a losing position?

#### Part 6:

- In your opinion, what role did emotions play in this experience?
- After a session in which several of your decisions proved unsuccessful, how did you react emotionally and how did this influence the next session?
- Did you notice any changes in your emotions or behaviour after several consecutive losses?





- Do you feel that your emotions have changed the way you structure your strategy over time?

## Part 7:

- Before placing an order, what emotions did you generally feel?
- Can you describe a situation where your emotions directly influenced your decision-making, whether in the context of a loss or a gain?
- Have you ever managed to make a good decision despite feeling stressed or anxious?
- Do you feel that your emotions have changed the way you structure your strategy over time?

## Part 8:

- How did you react to a loss?
- Did the losses affect your behaviour or decisions?
- How did you react to a gain?
- Did you then react more impulsively?

## Part 9:

- How did you handle the pressure of having to make decisions quickly?
- Did the breaks between each session influence your emotions?

## Appendix 2: Descriptive Statistics from Semi-Structured Interviews

Student	Duration	Number of words	Number of pages
I.1	42 min	4466	10
I.2	42 min	6827	12
I.3	59 min	7922	14
I.4	36 min	5946	11
I.5	43 min	7492	12
I.6	36 min	6124	11
I.7	42 min	5949	12
I.8	33 min	5577	10
Total	333 min	50,303	92
Average	42 min	6288	11.5
Max	59 min	7922	14
Min	33 min	4466	10
Standard deviation	8	1102	1.3