

Emotional Drivers of Financial Decision-Making: Unveiling the Link between Emotions and Stock Market Behavior (Part 2)

**Pr. Alain Finet^{1*}, PhD. Kevin Kristoforidis^{2*}, Julie Laznicka
(Doctoral Researcher)^{2*}**

^{1,2} Health Institute, Financial Management Department, University of Mons, Mons, Belgium
Correspondence: alain.finet@umons.ac.be; kevin.kristoforidis@umons.ac.be; julie.laznicka@umons.ac.be.

Abstract

This study is the second part of a three-part analysis (if it meets the review requirements) of emotions carried out by written documents. These documents were collected from eight students who took part in a three-day stock market experiment in January 2025. In the first part of this research (1), which was previously published, a lexical approach was used to analyze the words' emotional weight in the passages of the written documents. In this study, we considered all the passages in order to analyze a single written document for each student. To analyze the emotional charges in the documents, three Artificial Intelligences (ChatGPT, Gemini, and DeepSeek) have been used, and six queries have been selected. Using emotional couples, our results suggest different analytical processes depending on the Artificial Intelligence requested and a lack of uniformity in the emotional couples generated, according to the queries selected. At least, Artificial Intelligences are able to identify a strong primary and basic emotional trend but seem to have trouble capturing more nuanced emotional levels in a consistent manner. Using multiple queries does not improve the consistency of the results, and, indeed, the most generic query leads to the most uniform results among the selected artificial intelligences.

Keywords: Emotions, Individual Investors, Qualitative Research, Decision- Making, Artificial Intelligence

1. Introduction

Approaches that integrate Artificial Intelligence into qualitative research are still relatively underrepresented in literature, which can be attributed to their recent emergence. Morgan (2023) recently investigated the potential application of Artificial Intelligence, such as ChatGPT, in qualitative data analysis (2). It evaluates whether ChatGPT can replicate the themes identified in previous qualitative studies and concludes that it performs adequately for concrete themes but struggles with more nuanced ones. The study emphasizes ChatGPT's user-friendliness and the potential time savings it offers compared to manual coding. The author suggests that while

ChatGPT can serve as a valuable tool, it should be integrated into a broader analytical framework and has the potential to challenge the traditional dominance of manual coding in qualitative research: AI would hold considerable promise for qualitative analysis when applied appropriately. Since qualitative research involves reducing data into codes and categories to facilitate synthesis and interpretation, AI could serve as a valuable tool for generating codes (3), provided that queries and parameters are carefully controlled to align with the specific focus of the research (4). Furthermore, analyses highlight the significance of prompt design—for instance, when using platforms like Amazon Mechanical Turk, a question asking whether a word is associated with an emotion tends to yield more accurate results than asking if a word evokes an emotion (5). Contributions from qualitative research (2, 6) underscore the potential time savings associated with the use of Artificial Intelligence, particularly when compared to the time required for manual coding while adhering to a rigorous analysis process (7). However, AI is generally more effective at identifying specific, non-interpretative themes rather than more subtle, complex ones. Therefore, Artificial Intelligence is likely to be most beneficial in the early stages of analysis, such as in creating causal link diagrams (8). When it comes to emotion recognition, the complexity and nuanced nature of emotions, combined with the ambiguity of emotional boundaries and the incomplete nature of emotional data, makes this distinction particularly significant, complicating the task of categorizing emotions within specific categories (9). The success of AI-driven qualitative analysis would also depend on the precise presentation of the analytical context, adherence to the selected methodological framework, and clear definitions of data formats (10-11). Our search question will be written as follows. One of the limitations of Artificial Intelligence is its inability to generate emotion (12), so the question that naturally comes to mind is its ability to perceive, name, and even measure emotions.

Do artificial intelligence systems facilitate the reliable identification of emotional patterns in written texts, regardless of the AI model used?

2. Methodological Approach, Analysis Procedure and State of the Art

To address our research question, we analyze written data collected from eight students enrolled in Management Sciences at the University of Mons (Belgium), who participated in an experiment on trading over three consecutive days (from January 27 to 29, 2025). Using student experimental finance is a well-established approach (13-16). However, as noted by Dorn and Sengmueller (2009), students who are not directly motivated by the financial value of portfolios could overtrade (17). To address this limitation, the adaptations outlined below have been implemented.

The selection of participants was primarily influenced by financial constraints (students were paid). During the three days of the experiment, participants were asked to place trades based on a portfolio consisting of 40 French stocks (CAC40 index) and a virtual capital of 100,000 euros. No specific instructions were provided regarding the number of trades or their volume. Additionally, the highest financial portfolio was rewarded to encourage the development of differentiated emotional patterns over time. The decision-making experiments conducted since 2019 contributed to the refinement and enhancement of our experimental protocols.

Our methodology is based on experimental finance and supported by qualitative analysis tools. Morgan and Hoffman (2021) examine the direction of qualitative-oriented mixed-methods research by analyzing citations (18). The authors coded more than 200 empirical studies citing this article to determine the types of research designs used. The results support the idea of quantitative predominance in mixed methods research. In conclusion, qualitative-oriented mixed methods research remains largely underused. Even if qualitative studies are still less used than quantitative studies, several studies suggest that they should be given greater consideration, particularly when an understanding of human reality is needed (19). Using a combined orientation (experimental finance and qualitative analysis) reflects an evolution in the field of financial research. Indeed, in the '80s, Grether (1981) noted that experimentation was generally conducted by researchers in psychology but very little in finance (20). Under the influence of behavioral finance and better control of some technological tools, research methods have tended to shift (21). Bloomfield and Anderson (2009) also argue that experimentation is underused in the financial field but would be useful for testing behavioral finance and biases (22).

The material collected at the end of this experiment included trading notebooks, data collected through participant observation, semi-structured interviews, as well as written documents at the end of the experiment aimed at presenting how the experiment had been emotionally experienced by the participants. For answering our research question, we will mainly focus on this last material. The documents were written spontaneously, just after the end of the experiment, so that the emotional connotation was clearly present. The authors were free to choose their format, except that they had to focus on the emotional aspects: no instructions were given regarding the length of the documents (and in fact the documents vary greatly in length, Table 1) or the presentation of the reasons for motivation.

Table 1. Number of Words in Written Documents

Participant	Number of Words
1	325
2	69
3	151
4	287
5	229
6	249
7	215
8	74

All written documents were processed by three Artificial Intelligences (ChatGPT, Gemini and DeepSeek). In order to achieve a high level of understanding of what was required, we selected a series of six queries: the first two were very general and focused on identifying central emotions in the written documents, the third provided details on the kind of emotions to be analyzed (anger, anticipation, disgust, fear, happiness, sadness, surprise and optimism), the

fourth presented the general context in which the written documents were collected (three days of continuous trading), the fifth provided details on the work environment (a negative stock market context) and the sixth took into account the gender of the writer (male or female). The aim is to get an increasingly accurate picture of the emotions detected by the Artificial Intelligences after each query. Through this approach, we are following the recommendations provided by Zhang et al., 2024 (10). Bibliographical references will mainly be mentioned as the queries are being presented.

The queries were structured as follows:

Query 1: Considering the written document, what is the main emotion that arises?

This query aims at providing an overall view of the emotional orientation of the written document, without taking the prevailing context into consideration. Emotions in a text could be detected using an emotion lexicon (such as the NRC Emotion Lexicon), which is based on a database associating words with specific emotions. Some models (such as EmoLex) would also be able to recognize emotions by analyzing examples that have already been categorized (5). These tools nevertheless have limitations since the emotion expressed is not just summarized using fixed terminology (23). Moreover, they depend strongly on the quality and diversity of words or examples imported (24). Using Artificial Intelligence would therefore integrate linguistic, contextual or affective knowledge to understand the emotions in a text (25).

Query 2: Identify the two main emotions expressed in the written document.

This query aims at producing a more nuanced view of the written document's emotional orientation, without taking the prevailing context into consideration. The objective is to determine to what extent the two emotional components have the same charge (positive, neutral or negative). One sentence can actually combine several emotions and, as opposed to traditional approaches, artificial intelligence can identify emotional nuances (26).

Query 3: Considering the following eight emotions: anger, anticipation, disgust, fear, happiness, sadness, surprise and optimism, which are the key emotions in the written document? Give me the corresponding percentages and make sure that the sum of the percentages is equal to one. Give me a summary of the percentages.

Through this query, we try to identify all the emotional forces in the written document (positive, neutral and negative) and to achieve a higher degree of detail than in the previous query. It should be noted that, compared to the initial classification, we have replaced confidence with optimism because confidence could be understood by Artificial Intelligence as a positive emotion (overconfidence) or a negative emotion (lack of confidence). In the chosen classification, confidence has a positive connotation. In order to avoid the building of a category 'other emotions', the Artificial Intelligences only had to take into consideration the given emotions and produce a cumulative percentage equal to one. No elements related to the environment are considered here.

The first three queries deal with general issues; resulting analyses and conclusions involved may

be disconnected from the emotional reality of the environment. The last three queries will aim to define the context in which the emotions arose: we will therefore provide the Artificial Intelligences with the general context of the analysis (trading on the stock markets over a period of three days), the configuration of the markets during the experiment and, finally, we will focus on a specific socio-demographic factor central to understanding decision-making on the stock markets, namely the person's gender.

Query 4: Do the same work based on the same written document, but knowing that it was written following a three-day stock market experience.

The purpose of this query is to specify the environment from which the written feedback was drawn. Trading activities and the resulting decision-making processes take place in a specific context where emotions can play a central role. Because of the amount of information on the stock markets and the limited cognitive capacities of individual investors, emotions act as decision-making vectors and influence how people assess risky situations (27-29). In addition, emotions affect the perception of gains and losses, as well as the behaviors associated with financial results (30). For this purpose, emotional reactions related to the consequences of decisions made could lead to impulse buying or risky investments (31).

By insisting on the duration of the experience, Artificial Intelligences also consider the changes in feelings over the three days. Indeed, some students clearly expressed the emotional peaks considered as central and some were more important at very specific times.

Query 5: Conduct the same work on the same text in the same general environment and take into account that the stock market context was bearish during the experiment.

Our experiment took place during a bear market, even if the losses were relatively small, as shown in Table 2.

Table 2. CAC 40 Index, DJ30 Index, NASDAQ 100 Index and TOPIX Index Performance over the Experimentation Period.

Date	January 27, 2025	January 28, 2025	January 29, 2025	Total
CAC 40	-0,0003	-0,00012	-0,0032	-0,0036
DJ 30	0,0065	0,0031	-0,0031	0,0065
NASDAQ 100	-0,0297	0,0159	-0,0024	-0,0162
TOPIX	0,0026	-0,0004	0,0068	0,009

This query provides more precise information on the decision-making context and the related emotional charges. In a bear market, an increase in negative emotions, such as fear and anxiety (32), can be noticed, especially when the configuration has changed little over the three days. Taffler et al. (2024) also highlight that a bearish market is mainly dominated by anxiety-related emotions (33). The motivation process also differs according to the negative emotion felt. Thus, anger and sadness do not constitute a barrier to decision-making on the stock markets, while disgust and fear encourage individual investors to reduce their transactions (34).

Query 6: Do the same work on the same text in the same general environment, taking into

account that the stock market context was negative during the experiment and that the gender of the person who wrote the document was M/F.

The latest query aims at analyzing how Artificial Intelligence deals with a person's gender when processing decision-making, specifically on the bearish stock markets. Gender differences in explaining people's behavior and decisions on the stock markets have been widely documented (35-37).

Literature generally emphasizes that men tend to take part in the stock market more than women, as women are more averse to loss than men (38). Moreover, how the information available on the stock markets is processed also varies according to the gender of the individual investor. In fact, men are said to interpret both favorable and unfavorable information in a more optimistic way than women (39). This difference could be explained as men are more likely to overestimate their knowledge and therefore be affected by overconfidence and optimism (40).

On the other hand, the female population is said to be more concerned with the uncertainty and consequences of decisions taken on the stock markets (41). Gender could also help explain differences in the emotions expressed by individual investors. More specifically, women seem to be less influenced by emotions related to past financial results and those related to expectations of future financial performance (42). In contrast to men, who, due to their higher risk propensity and because they carry out a larger volume of transactions, are more likely to have large emotional fluctuations.

The queries were used in the same format for all Artificial Intelligences and the results were generated during a single work session per Artificial Intelligence in order to provide a continuous process in the AI analysis.

3. Results

The transition from one query to the next resulted in changes in the percentages for the different emotions identified by Artificial Intelligences. The different reasons explaining the changes are detailed below for one participant, Artificial Intelligence per Artificial Intelligence. All the comments below, shown in italics, come directly from what was generated by the three Artificial Intelligences.

ChatGPT Adjustments

Query 3 to Query 4

Taking into account the context of a stock market experience lasting three days, we can reassess the emotions in the text. The stock market experience involves a process of analysis, waiting for results and managing successes and failures, which influences the emotions expressed.

Here are the main emotions adjusted:

Anger: Frustration related to the inability to act or the ineffectiveness of past actions (failure to achieve objectives) can be considered as anger in this context.

Anticipation: In the stock market, anticipation of market moves and planning are essential, which justifies a higher percentage for this emotion.

Disgust: This feeling arises from the disappointment at the lack of positive results after hoping for a market turnaround.

Happiness: This emotion arises when a positive result (being in first place thanks to your portfolio) is achieved at the end of the experiment.

Sadness: This emotion arises from disappointments during the experiment, particularly when the market does not follow the forecasts.

Surprise: The experiment seems relatively predictable, with expected results based on the analyses, so there is less surprise.

Fear: Although there are uncertainties in the stock market experiment, fear is not explicitly expressed in the text.

Optimism: Optimism is a persistent hope, despite the challenges faced during the experiment.

Query 4 to 5

If we consider that the stock market context was negative during the experiment, this changes the analysis of emotions, because the challenges of a bear market environment amplify emotions such as frustration, disgust and sadness. Optimism and happiness will probably be less present, given the disappointing results.

Query 5 to Query 6

Considering that the writer of the document is male, the expression of emotions can be influenced by cultural or social norms, but this does not necessarily change the emotions themselves, especially in a context as technical and professional as the stock market experience. However, if we consider the general trends in the way emotions are expressed in this type of context, we could suggest that some emotions, such as anger or frustration, may be more intense, while emotions such as happiness or optimism may be less visible.

Gemini Adjustments

Query 3 to Query 4

If we consider that the document was written following a three-day stock market experience, this exacerbates some emotions and mitigates others.

The changes made were as follows: the emotion of fear was increased. Anger was added.

These changes reflect the potential impact of a short-term stock market experience on the author's emotional state.

Query 4 to Query 5

Let's consider the context of a three-day negative stock market experience to refine the analysis of emotions: fear becomes the dominant emotion, reflecting anxiety about a persistently negative market. Anger increases, reflecting frustration caused by repeated losses. Anticipation is developing, even if only to a small extent. The rest of the negative emotions have been rebalanced in relation to the increases in fear and anger. This distribution highlights the significant impact of a negative stock market context over a short period, intensifying negative

emotions and attenuating others.

Query 5 to Query 6

Let's consider the gender of the author (a man) in this specific context of a three-day negative stock market experience: although the basic emotions are universal, some studies suggest that men may express or internalize emotions differently. Anger increases, reflecting a potential tendency to express this emotion. Sadness decreases slightly. This distribution considers the potential nuances in the expression of emotions related to gender, corresponding to the experience.

DeepSeek Adjustments

Query 3 to Query 4

- Day 1 → Day 3: Transition from anger to sadness
- Residual optimism as a defense mechanism
- Growing but contained fear (12%)

Typical of a trader in a phase of resignation.

Query 4 to Query 5

The bear market transforms the experience into:

1. Financial grief (45% sadness)
2. Institutionalized fear (20%)
3. Externalized anger (15%)

Positive emotions become residual (<7%), replaced by:

- Disgust (8%) as a protective mechanism
- Zero surprise (permanent anticipation of the worst)

Typical of the “trapped trader” syndrome.

Query 5 to Query 6:

The male trader shows:

A hyper-technicalization of emotions (figures > feelings), increased self-directed anger, sadness expressed indirectly through losses, fear minimized because it is perceived as a “weakness”.

Before going into the results, some comments should be made on the data processing by the Artificial Intelligences. From query 3 to query 6, Gemini concentrates on a relatively small number of emotional labels and in some cases leaves out emotions that are only marginally detected by the other two Artificial Intelligences. In any case, this does not affect the ranking of the main emotions, but it demonstrates a less nuanced vision for Gemini. In some cases, Gemini's emotional interpretation seems very rigid (this is particularly the case for the shortest written documents). On the one hand, some emotional nuances may be less effectively detected by Gemini. On the other hand, the other two Artificial Intelligences may also be said to produce emotional hallucinations by offering emotional percentages of less than 5%. Accordingly, we decided to work in terms of emotions couples. In the remainder of the article, the first component of the combination will correspond to the emotion with the highest percentage as determined by Artificial Intelligences, and the second to the emotion in second place.

Moreover, basically, although this is more present for DeepSeek than for the other two Artificial Intelligences, the transition from query 5 to query 6 (i.e. the one corresponding to taking the person's gender into account) leads to a reinforcement of the negative connotation of emotions and the omnipresence of anger (fear to anger, sadness to anger).

Furthermore, in only one case, Gemini mentions disgust in the analysis (whether as the main or secondary emotional label) and we note that, in this case, this emotion also emerges very strongly from ChatGPT and DeepSeek. Our findings show that disgust is distributed much more uniformly among the other Artificial Intelligences. This could be explained due to the different definitions used by Artificial Intelligence for this specific emotion, and, in the “mind” of Gemini, disgust could be assimilated with other close emotions.

Table 3. Overview of the Main Emotional Trend (Query 1) and Emotional Combinations according to the Selected Query (Query 2 to Query 6)

	AI	Q1	Q2	Q3	Q4	Q5	Q6
1	GPT1	Frustration	Frustration, Resignation	Anticipation, Anger	Anticipation, Anger	Anger, Disgust	Anger, Anticipation
	GEM2	Regret	Regret, Anxiety	Surprise, Fear	Fear, Surprise	Fear, Anger	Anger, Fear
	DSK3	Regret	Regret, Resignation	Sadness, Optimism	Sadness, Optimism	Sadness, Anger	Anger, Sadness
2	GPT	Disappointment	Disappointment, Frustration	Disgust/Fear, Sadness	Disgust, Sadness/Fear	Anger, Disgust	Anger, Fear
	GEM	Regret	Regret, Disappointment	Sadness/Fear, Surprise	Fear, Sadness	Fear, Sadness	Anger, Fear
	DSK	Disappointment	Disappointment, Resignation	Sadness, Surprise	Sadness, Surprise	Sadness, Disgust	Anger, Disgust
3	GPT	Frustration	Frustration, Optimism	Disgust/Anticipation, Anger	Disgust, Anger	Disgust, Anger	Disgust, Anger
	GE M	Frustration	Frustration, Optimism	Optimism, Happiness	Fear, Sadness	Fear, Sadness	Fear, Anger/Sadness
	DSK	Frustration	Frustration, Disgust	Disgust/Anger	Disgust/Anger	Disgust/Anger	Anger, Disgust
4	GPT	Disgust	Disgust, Frustration	Disgust, Anger	Disgust, Anger	Disgust, Anger	Disgust, Anger

	GEM	Disgust	Disgust, Surprise	Disgust, Surprise	Disgust, Surprise	Fear, Disgust	Fear, Anger/Dis gust
	DSK	Disgust	Disgust, Surprise	Disgust, Surprise	Disgust, Sadness	Disgust, Sadness	Anger, Disgust
5	GPT	Frustration	Frustration, Disappointment	Anticipation, Disgust	Anticipation, Disgust	Disgust/Anticipation, Anger	Disgust, Anger

1 ChatGPT

2 Gemini

3 DeepSeek

	GEM	Frustration	Frustration, Disappointment	Anger, Sadness	Anger, Sadness	Anger, Fear	Anger, Fear
	DSK	Frustration	Frustration, Euphoria	Sadness, Anger	Sadness, Anger	Sadness, Fear	Anger, Sadness
6	GPT	Fear	Fear, Surprise	Fear, Disgust	Fear, Disgust	Fear, Disgust	Fear, Disgust
	GEM	Surprise	Fear, Resignation	Surprise, Fear	Surprise, Fear	Fear, Sadness	Fear, Sadness
	DSK	Fear	Fear, Surprise	Fear, Surprise	Fear, Surprise	Fear, Sadness	Anger, Fear
7	GPT	Frustration	Frustration, Anticipation	Sadness, Disgust	Anticipation, Disgust	Disgust, Anger	Disgust, Anger
	GEM	Regret	Frustration, Disappointment	Sadness, Fear	Sadness, Fear	Fear, Sadness	Sadness, Fear
	DSK	Frustration	Frustration, Regret	Sadness, Anger	Sadness, Anger	Sadness, Fear	Sadness, Fear
8	GPT	Frustration	Frustration, Disappointment	Anticipation, Happiness	Anticipation/Happiness, Disgust	Disgust, Anticipation/Fear, Anger	Disgust/Fear, Anger
	GEM	Regret	Regret, Relief	Sadness, Surprise	Sadness, Surprise	Fear, Sadness	Anger, Fear
	DSK	Frustration	Frustration, Anxiety	Sadness, Fear	Sadness, Fear	Sadness, Fear	Anger, Fear

For the three Artificial Intelligences selected, a large number of negative emotions were detected, and this negative trend increased with each query (from query 2 to query 6). In the second query, in which Artificial Intelligences were free to choose the main emotions, unusual positive emotions (relief and euphoria) were generated. Subsequently, according to the third query, there is a focus on the eight predefined emotions, with a large under-representation of positive ones. Emotions polarities were defined as follows:

Table 4. Definition of Emotional Polarity

Emotions	Polarity
Optimism	Positive (+)
Happiness	Positive (+)
Anticipation	Neutral
Surprise	Neutral
Sadness	Negative (-)
Fear	Negative (-)
Anger	Negative (-)
Disgust	Negative (-)

By working on the basis of emotional couples, Artificial Intelligences never achieve the same results, whatever the query. Our results demonstrate a basic trend, a relatively stable negative emotional pattern from every query (we had noticed it informally during the experiment, and the results generated by the Artificial Intelligences only confirm what we felt), but they do not provide a clear picture of the emotional complexity required to understand specific behavioral dynamics : the two elements in the emotional combinations are rarely the same or are placed differently in the couples, even if their negative charge is the same. It is interesting to note that the only homogeneous results were achieved from the first query, where Artificial Intelligences chose by themselves the most present emotion in the written documents. The more levels of details are requested, the less coherent the results become for the whole emotional picture. According to this first result, we will now turn to emotional polarities in couples.

Table 5. Overview of the Main Emotional Trend (Query 1) and Emotional Combinations according to the Selected Query (Query 2 to Query 6) and Emotional Polarity (All Queries).

	AI	Q1	Q2	Q3	Q4	Q5	Q6
1	GPT	-	(-, -)	(Neutral, -)	(Neutral, -)	(-, -)	(-, neutral)
	GEM	-	(-, -)	(Neutral, -)	(-, Neutral)	(-, -)	(-, -)
	DSK	-	(-, -)	(-, +)	(-, +)	(-, -)	(-, -)
2	GPT	-	(-, -)	(-/-, -)	(-, -/-)	(-, -)	(-, -)
	GEM	-	(-, -)	(-/-, Neutral)	(-, -)	(-, -)	(-, -)
	DSK	-	(-, -)	(-, Neutral)	(-, Neutral)	(-, -)	(-, -)
3	GPT	-	(-, +)	(-/Neutral, -)	(-, -)	(-, -)	(-, -)

	GEM	-	(-,+)	(+,+)	(-,-)	(-,-)	(-,-/-)
	DSK	-	(-,-)	(-,-)	(-,-)	(-,-)	(-,-)
4	GPT	-	(-,-)	(-,-)	(-,-)	(-,-)	(-,-)
	GEM	-	(-, Neutral)	(-, Neutral)	(-, Neutral)	(-,-)	(-,-/-)
	DSK	-	(-, Neutral)	(-, Neutral)	(-,-)	(-,-)	(-,-)
5	GPT	-	(-,-)	(Neutral, -)	(Neutral, -)	(- /Neutral,-)	(-,-)
	GEM	-	(-,-)	(-,-)	(-,-)	(-,-)	(-,-)
	DSK	-	(-,+)	(-,-)	(-,-)	(-,-)	(-,-)
6	GPT	-	(-,Neutral)	(-,-)	(-,-)	(-,-)	(-,-)
	GEM	Neutral	(-,-)	(Neutral,-)	(Neutral,-)	(-,-)	(-,-)
	DSK	-	(-,Neutral)	(-,Neutral)	(-,Neutral)	(-,-)	(-,-)
7	GPT	-	(-,Neutral)	(-,-)	(Neutral,-)	(-,-)	(-,-)
	GEM	-	(-,-)	(-,-)	(-,-)	(-,-)	(-,-)
	DSK	-	(-,-)	(-,-)	(-,-)	(-,-)	(-,-)
8	GPT	-	(-,-)	(Neutral,+)	(Neutral/+,-)	(- ,Neutral/- , -)	(-/-,-)
	GEM	-	(-,+)	(-,Neutral)	(-,Neutral)	(-,-)	(-,-)
	DSK	-	(-,-)	(-,-)	(-,-)	(-,-)	(-,-)

By considering the polarity of the emotion (query 1) and the emotions inside the emotional combinations (queries 2 to 6), we find relatively homogeneous results for the first query. However, for the emotional combinations from query 2 to query 6, we have to consider query 5 (the Stock Market was bearish during the experiment) to find a higher level of homogeneity. Note that the highest level is achieved when the person's gender is taken into consideration (query 6).

Table 6. Overview of the General Emotional Trend (Query 1 and Query 2), no Reference to the Chosen Classification for Queries 3 to 6 (all AI)

Emotion	Query 1	Query 2
Frustration	11	14
Regret	5	5
Disappointment	2	7
Disgust	3	4
Fear	2	4
Surprise	1	4
Euphoria		1
Resignation		4
Relief		1

Anxiety		2
Optimism		2
Total	24	48
Emotions	Query 1	Query 2
Positive Emotions	0	4
Neutral Emotions	1	4
Negative Emotions	23	40
Total	24	48
Emotions (%)	Query 1	Query 2
Positive Emotions	0	0,083
Neutral Emotions	0,041	0,083
Negative Emotions	0,959	0,833
Total	1	1

Table 7. Overview of the General Emotional Trend (from Query 3 to Query 6), Including all the Components in the Emotional Combinations (see Table 3)

Emotions	Query 3	Query 4	Query 5	Query 6	Total	Percentage
Optimism	2	1	0	0	3	0,0148
Happiness	2	1	0	0	3	0,0148
Anticipation	4	4	2	1	11	0,0542
Surprise	8	6	0	0	14	0,069
Sadness	11	12	12	6	41	0,202
Fear	8	9	14	14	45	0,2216
Anger	7	7	11	20	45	0,2216
Disgust	9	10	12	10	41	0,202
Total	51	50	51	51	203	1

Table 8. Summary of the Emotional Polarities for all Emotions from Queries from 3 to 6 (all AI)

Emotion Polarity	Positive Emotions	Neutral Emotions	Negative Emotions
Percentage	0,0296	0,1231	0,8473

From the analysis of all the queries together, our results reveal that 85% of the emotions expressed have negative charges (whatever their position in the combination), and only 3% of the emotions are considered positive. This result - very similar from one AI to another from query 5 - suggests a negative emotional atmosphere. This could be explained by the stock market context prevailing during the experiment and the series of disappointments that followed, as a result of financial expectations not being met.

Table 9. Changes in Emotional Polarities in Response to the Queries (Query 3 to Query 6, all AI)

Emotional Polarity (Number)	Query 3	Query 4	Query 5	Query 6
Positive Emotions	4	2	0	0
Neutral Emotions	12	10	2	1
Negative Emotions	35	38	49	50
Total	51	50	51	51
Emotions Polarity (%)	Query 3	Query 4	Query 5	Query 6
Positive Emotions	0,0784	0,04	0	0
Neutral Emotions	0,2353	0,2	0,039	0,0196
Negative Emotions	0,6863	0,76	0,961	0,9804
Total	1	1	1	1

By taking all the components of the emotional couples for the three Artificial Intelligences, we notice a significant increase in the percentage of negative emotions as the queries are selected. The most significant increase is found between query 4 and query 5, i.e. when the Stock Market's negative trend during the experiment is considered. From query 5, no more positive emotions are detected by Artificial Intelligences, and in the last query (query 6) only the anticipation (considered neutral with a double emotional charge) was noticed on one occasion.

4. Conclusion and Discussions

Qualitative studies could be based on several types of signals (written, verbal, physical and physiological). Until recently, their analysis was time-consuming and required a formalized approach using analysis grids. Qualitative studies aim to understand psychological, emotional and behavioral issues that are not easily measurable. They can, for example, identify correspondence between some observations and construct typologies that could, however, be corroborated by quantitative tools. Artificial Intelligences accelerated data processing, particularly for highly accurate elements. Regarding the question of whether Artificial Intelligence can replace human data analysis (43), the answer we provide is more than inconclusive. In the case of this study, based on documents written following a trading experiment, we analyzed how Artificial Intelligence was able to identify the emotions expressed in these documents. Indeed, when Artificial Intelligences process queries, they both can generate different emotional responses, depending on the queries. The problem is that, as the number of queries increases, the results generated by the Artificial Intelligences become increasingly divergent. The results from the first queries (the least structured) reveal relatively stable primary emotional tendencies from one Artificial Intelligence to another. The lack of uniformity in the results becomes increasingly important when emotional nuances are explored, namely when using emotional combinations. In this case, the processing carried out by Artificial Intelligences differ from one to another and the results generated become less and less consistent: we will not use the expression “emotional hallucinations” because the results remain

relatively constant within the same Artificial Intelligence; on the other hand, the comparison of the findings results in a more complex analysis and in confusion in the emotional interpretation. And so, according to us, Artificial Intelligences facilitate the identification of major trends and emotional charges (even if they must be verified by more ‘human’ analyses) but are unable to address more nuanced and sensitive aspects, particularly because their analyses are based on personally tailored protocols. We suggest that, depending on the selected generative tool, researchers could draw conclusions that best match their personality: the question arises of the researcher's reflexivity (44) and their personal emotional positioning (45). Finally, by working on the basis of emotional couples, the unresolved question remains of the simultaneous influence of the two emotional labels. For example, in a couple where anticipation (neutral emotion) comes second after a negative emotion, the question arises as to what extent an unconfirmed positive anticipation could have facilitated the development of the negative emotion.

In conclusion, even if Artificial Intelligence results in significant time savings and even if it facilitates initial data processing, it cannot replace human judgment and manipulation. In terms of methodological guidelines, in order to gain granularity, we recommend using several queries and a combined analysis of the reasons given by the Artificial Intelligences to explain changes in the results between two queries. This work, carried out by human intervention to study the correspondence between what is generated by Artificial Intelligence and the related theory, helps to adjust the queries selected. For example, in our study, the question could be: is it theoretically justified that DeepSeek systematically changes a moderate negative emotion (sadness and fear identified in query 5) into a much more intense negative emotion (anger) because it takes the person's gender into account (query 6)? While Gemini and ChatGPT don't necessarily make this change. If not, the analyses should stop at query 5 for the three Artificial Intelligences and should only consider the results of query 6 for Gemini and ChatGPT. This procedure necessarily increases the analysis time but, on the other hand, guarantees a higher degree of consistency between what is generated and the relevant theoretical background. In our opinion, this is the best way to guarantee the smart use of Artificial Intelligence. Our results support previous findings which emphasize the supportive role of artificial intelligence and argue that it cannot be used as a measuring tool to generate conclusions and universal truths.

5. Limitations

Firstly, our results are based on a small number of written documents, drafted in a specific decision-making context. Secondly, these documents were relatively short (they were written spontaneously, from a first-hand perspective, following three days of trading), thus facilitating the identification of main emotional trends but not necessarily made for an accurate assessment of more nuanced emotional charges that might arise from longer written documents. If the Artificial Intelligences are not able to identify more nuanced emotional charges homogeneously,

it could be explained by textual formats which do not facilitate process of an adequate level of precision. Thirdly, two emotions were considered neutral (surprise and anticipation) because they can theoretically be associated with neutral (both positive and negative) emotional charges (a good surprise versus a bad surprise, a positive or a negative anticipation). In order to highlight the emotional aspects related to these emotions, the third part of this research will be devoted to separating them (a positive component and a negative component). This work will give us a better view of emotional orientation (namely for the first queries), focusing only on positive and negative emotional connotations related to the written documents. Finally, we will also take into consideration the competitive aspect of the experience (the fact that the highest financial portfolio has been rewarded) in a separate query.

To be continued...

References

1. Finet A, Kristoforidis K, Laznicka J. Emotional drivers of financial decision-making: unveiling the link between emotions and stock market behavior. *J Next-Gener Res.* 2025; 1(3). Available from: <https://doi.org/10.70792/jngr5.0.v1i3.103>
2. Morgan DL. Exploring the use of artificial intelligence for qualitative data analysis: the case of ChatGPT. *Int J Qual Methods.* 2023; 22:1–10. Available from: <https://doi.org/10.1177/16094069231211248>
3. Gielens E, Sowula J, Leifeld P. Goodbye human annotators? Content analysis of social policy debates using ChatGPT. *J Soc Policy.* 2025. Available from: <https://doi.org/10.1017/S0047279424000382>
4. Bryda G, Sadowski D. From words to themes: AI-powered qualitative data coding and analysis. In: *World Conference on Qualitative Research.* Cham: Springer Nature Switzerland; 2024. p. 309–45. Available from: https://doi.org/10.1007/978-3-031-65735-1_19
5. Mohammad SM, Turney PD. Crowdsourcing a word–emotion association lexicon. *Comput Intell.* 2013; 29(3):436–65. Available from: <https://doi.org/10.1111/j.1467-8640.2012.00460.x>
6. Salah M, Al Halbusi H, Abdelfattah F. May the force of text data analysis be with you: unleashing the power of generative AI for social psychology research. *Comput Hum Behav Artif Humans.* 2023;1(2). Available from: <https://doi.org/10.1016/j.chbah.2023.100006>
7. Özden M. Content and thematic analysis techniques in qualitative research: purpose, process and features. *Qual Inq Educ Theory Pract.* 2024;2(1):64–81. Available from: <https://doi.org/10.59455/qietp.20>
8. Jalali M. Integrating AI language models in qualitative research: replicating interview data analysis for creating causal loop diagrams. *Syst Dyn Rev.* 2024. Available from: <https://doi.org/10.1002/sdr.1772>
9. Deng J, Ren F. A survey of textual emotion recognition and its challenges. *IEEE Trans Affect Comput.* 2021;12(4):3013–37. Available from: <https://doi.org/10.1109/TAFFC.2021.3053275>
10. Zhang H, Wu C, Xie J, Lyu Y, Cai J, Carroll JM. Redefining qualitative analysis in the AI era: utilizing ChatGPT for efficient thematic analysis. 2024. Available from:

<https://doi.org/10.48550/arXiv.2309.10771>

11. Zhang F, Chen J, Tang Q, Tian Y. Evaluation of emotion classification schemes in social media text: an annotation-based approach. BMC Psychol. 2024;12:503. Available from: <https://doi.org/10.1186/s40359-024-02008-w>

12. Vicci H. Emotional intelligence in artificial intelligence: a review and evaluation study. SSRN Electron J. 2024 May. Available from: <https://doi.org/10.2139/ssrn.4818285>

13. Ackert LF, Church BK, Tompkins J, Zhang P. What's in a name? An experimental examination of investment behavior. Rev Finance. 2005;9(2):281–304. doi:10.1007/s10679-005-7594-2

14. Biais B, Hilton D, Mazurier K, Pouget S. Judgemental overconfidence, self-monitoring, and trading performance in an experimental financial market. Rev Econ Stud. 2005;72(2):287–312. doi:10.1111/j.1467-937X.2005.00333.x

15. Bruguier AJ, Quartz SR, Bossaerts P. Exploring the nature of “trader intuition”. J Finance. 2010;65(5):1703–23. doi:10.1111/j.1540-6261.2010.01591.x

16. Widiyarni I. The role of negative moral emotions (anger and disgust) in ethical decision making. In: 8th International Conference of Asian Association of Indigenous and Cultural Psychology (ICAAIP 2017). Atlantis Press; 2017. p. 244–50. doi:10.2991/icaaip-17.2018.57

17. Dorn D, Sengmueller P. Trading as entertainment. Manag Sci. 2009;55(4):591–603. Available from: <https://doi.org/10.1287/mnsc.1080.0962>

18. Morgan DL, Hoffman K. Searching for qualitatively driven mixed methods research: a citation analysis. Qual Quant. 2021;55(2):731–40. Available from: <https://doi.org/10.1007/s11135-020-01025-2>

19. Almas I, Lordos A. A narrative review of psychopathy research: current advances and the argument for a qualitative approach. J Forensic Psychiatry Psychol. 2025. Epub ahead of print. Available from: <https://doi.org/10.1080/14789949.2025.2456208>

20. Grether D. Financial incentive effects and individual decision-making. Soc Sci Working Pap. 1981;(401):1–13.

21. Ricciardi R. A risk perception primer: a narrative research review of the risk perception literature in behavioral accounting and behavioral finance. SSRN. 2004. Available from: <http://ssrn.com/abstract=566802>

22. Bloomfield R, Anderson A. Experimental finance. Johnson Sch Res Pap Ser. 2009;(23):1–22. doi:10.1002/9781118258415

23. Nandwani P, Verma R. A review on sentiment analysis and emotion detection from text. Soc Netw Anal Min. 2021;11(1):81. Available from: <https://doi.org/10.1007/s13278-021-00776-6>

24. Wake N, Kanehira A, Sasabuchi K, Takamatsu J, Ikeuchi K. Bias in emotion recognition with ChatGPT. arXiv Preprint. 2023. Available from: <https://doi.org/10.48550/arXiv.2310.11753>

25. Tu G, Liang B, Qin B, Wong KF, Xu R. An empirical study on multiple knowledge from ChatGPT for emotion recognition in conversations. In: Findings of the Association for Computational Linguistics: EMNLP 2023. 2023 Dec. p. 12160–73. Available from: <https://doi.org/10.18653/v1/2023.findings-emnlp.813>

26. Elyoseph Z, Hadar-Shoval D, Asraf K, Lvovsky M. ChatGPT outperforms humans in emotional awareness evaluations. Front Psychol. 2023;14. Available from: <https://doi.org/10.3389/fpsyg.2023.1199058>

27. Matsumoto D, Wilson M. Effects of multiple discrete emotions on risk-taking propensity. *Curr Psychol*. 2023;42(18):15763–72. Available from: <https://doi.org/10.1007/s12144-022-02868-8>
28. Agarwal V, Taffler RJ, Wang C. Investor emotions and market bubbles. *Rev Quant Financ Account*. 2024;1–31. Available from: <https://doi.org/10.1007/s11156-024-01309-w>
29. Finet A, Laznicka J. The decline and fall of the Homo Economicus: the urgent need of understanding emotions in financial decision-making. *Int J Soc Sci Humanit Rev*. 2025;13(1):145–55. Available from: <https://doi.org/10.5281/zenodo.14842758>
30. Duxbury D, Gärling T, Gamble A, Klass V. How emotions influence behavior in financial markets: a conceptual analysis and emotion-based account of buy-sell preferences. *Eur J Finance*. 2020;26(14):1417–38.
31. Camerer C, Loewenstein G, Prelec D. Neuroeconomics: how neuroscience can inform economics. *J Econ Lit*. 2005;43(1):9–64. doi:10.1257/0022051053737843
32. Wang H, Zhang J, Wang L, Liu S. Emotion and investment returns: situation and personality as moderators in a stock market. *Soc Behav Pers*. 2014;42(4):561–9. Available from: <https://doi.org/10.2224/sbp.2014.42.4.561>
33. Taffler RJ, Agarwal V, Obring M. Narrative emotions and market crises. *J Behav Finance*. 2024;1–21. Available from: <https://doi.org/10.1080/15427560.2024.2365723>
34. Harmon-Jones C, Bastian B, Harmon-Jones E. The discrete emotions questionnaire: a new tool for measuring state self-reported emotions. *PLoS One*. 2016;11(8). Available from: <https://doi.org/10.1371/journal.pone.0159915>
35. Finet A, Kristoforidis K, Viseur R. De la composante genre dans les activités de trading: une étude exploratoire. *Rev Sci Gest*. 2022;313:43–51. Available from: <https://doi.org/10.3917/rsg.313.0047>
36. Finet A, Laznicka J, Palumbo H. From which planet do they come from? Biases in trading strategies: does the gender matter. *Int J Bus Manag*. 2024;12(12):1–11. Available from: <https://doi.org/10.24940/theijbm/2024/v12/i12/>
37. Cueva C, Rustichini A. Is financial instability male-driven? Gender and cognitive skills in experimental asset markets. *J Econ Behav Organ*. 2015;119:330–44. Available from: <https://doi.org/10.1016/j.jebo.2015.08.014>
38. Holden ST, Tilahun M. Are risk preferences explaining gender differences in investment behavior? *J Behav Exp Econ*. 2022;101. Available from: <https://doi.org/10.1016/j.socrec.2022.101949>
39. Karmarkar UR. Gender differences in “optimistic” information processing in uncertain decisions. *Cogn Affect Behav Neurosci*. 2023;23(3):827–37. Available from: <https://doi.org/10.3758/s13415-023-01075-7>
40. Cueva C, Iturbe-Ormaetxe I, Ponti G, Tomás J. Boys will still be boys: gender differences in trading activity are not due to differences in (over)confidence. *J Econ Behav Organ*. 2019;160:100–20. Available from: <https://doi.org/10.1016/j.jebo.2019.02.027>
41. de Acedo Lizárraga MLS, de Acedo Baquedano MTS, Cardelle-Elawar M. Factors that affect decision making: gender and age differences. *Int J Psychol Psychol Ther*. 2007;7(3):381–91.
42. Gabbi G, Zanotti G. Sex & the City: are financial decisions driven by emotions? *J Behav Exp Finance*. 2019;21:50–7. Available from: <https://doi.org/10.1016/j.jbef.2018.10.005>
43. Kumar M. Emotion recognition in natural language processing: understanding how AI interprets

the emotional tone of text. J Artif Intell Cloud Comput. 2024;3(6):1–5. doi:10.47363/JAICC/2024(3)E238

44. Ide Y, Beddoe L. Challenging perspectives: reflexivity as a critical approach to qualitative social work research. Qual Soc Work. 2024; 23(4):725–40. Available from: <https://doi.org/10.1177/14733250231173522>

45. Lustick H, Yang X, Hakouz A. The role of emotions in qualitative analysis: researchers' perspectives. Qual Rep. 2024;29(4):1103–24. Available from: <https://doi.org/10.46743/2160-3715/2024.6232>

Appendices

Table 10. ChatGPT Presentation of Results

ChatGPT	190030/Emotions	P1	P2	P3	P4	P5	P6
	Frustration	×					
	Resignation	×	×				
	Anger			0,18	0,2	0,23	0,24
	Anticipation			0,2	0,22	0,19	0,21
	Disgust			0,15	0,16	0,21	0,2
	Fear			0,12	0,13	0,14	0,14
	Happiness			0,1	0,09	0,07	0,07
	Sadness			0,08	0,07	0,08	0,06
	Surprise			0,07	0,06	0,05	0,05
	Optimism			0,1	0,07	0,03	0,03

Table 11. Gemini Presentation of Results

Gemini	190030/Emotions	P1	P2	P3	P4	P5	P6
	Regret	×					
	Anxiety	×	×				
	Anger			0,15	0,2	0,3	0,35
	Anticipation			0,1	0,1	0,1	0,15
	Disgust			0	0	0	0
	Fear			0,3	0,35	0,4	0,3
	Happiness			0	0	0	0
	Sadness			0	0	0	0
	Surprise			0,4	0,3	0,2	0,2
	Optimism			0,05	0,05	0	0

Table 12. DeepSeek Presentation of Results

DeepSeek	190030/Emotions	P1	P2	P3	P4	P5	P6
	Regret	×					
	Resignation	×	×				
	Anger			0,1	0,1	0,18	0,35

	Anticipation			0,06	0,05	0,05	0,15
	Disgust			0,01	0	0,02	0,03
	Fear			0,12	0,12	0,15	0,12
	Happiness			0,04	0,03	0,03	0,02
	Sadness			0,45	0,4	0,45	0,25
	Surprise			0,02	0,02	0,02	0
	Optimism			0,2	0,15	0,1	0,08