



Emotional Drivers of Financial Decision-Making: Unveiling the Link Between Emotions and Stock Market Behavior (Part 3)

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Abstract

This study is the third part of a research project involving analyzing written documents to assess emotional charges. Those documents have been written following a three-day trading experience. The first part focused on the textual analysis of these documents using several measurement scales. The second part consisted of a comparative analysis of the results using three Artificial Intelligences (ChatGPT, Gemini, and DeepSeek), working through several queries designed to clarify the emotional fields under analysis as well as the general context that led to the documents being written. Our results demonstrated the ability of Artificial Intelligence to identify a general emotional context but revealed difficulties in approaching some emotional nuances. In this third study, we refined the queries addressed to the three Artificial Intelligences, particularly about the emotions to be taken into consideration, making a distinction between positive anticipation and negative anticipation, as well as a distinction between a good surprise and a bad surprise. The emotional typology used prevented us from considering how the two aspects could differ. Finally, the Artificial Intelligences were informed that a reward would be granted to the best-performing portfolio at the end of the experiment. Our results show that DeepSeek gives great importance to this parameter and generates many positive emotions, which neither ChatGPT nor Gemini do. Our results once again demonstrate a consistent ability of Artificial Intelligence to clarify the prevailing general emotional context, but difficulties in identifying consistently and uniformly the emotional nuances associated with the experiment. Concluding these three articles, it seems clear that Artificial Intelligences could be used to begin the process of understanding qualitative data, but it must be complemented by a human dimension in order to capture the emotional nuances that Artificial Intelligences analysis cannot.

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



1. Introduction

Approaches that integrate Artificial Intelligence (AI) into qualitative research are still relatively underrepresented in the literature, which can be attributed to their recent emergence. In the first part of our research project (1), we conducted a textual analysis of documents produced following a three-day trading simulation, utilizing various measurement scales to assess emotional content. The second part (2) involved a comparative analysis using three AI models—ChatGPT, Gemini, and DeepSeek—through multiple queries designed to elucidate the emotional dimensions and contextual factors influencing the documents. Findings indicated that AI models could identify overarching emotional contexts but struggled with nuanced emotional distinctions. Building upon these findings, the third study aims to refine the queries directed at the AI models, specifically distinguishing between positive and negative anticipation and between favorable and unfavorable surprises. Additionally, at the experiment's conclusion, the AI models were informed about a reward for the best-performing portfolio. Recently, Morgan (2023) investigates the potential application of Artificial Intelligence, such as ChatGPT, in qualitative data analysis (3). 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. Wachinger et al. (2024) investigate the use of ChatGPT in qualitative analysis by comparing its results with a human researcher (4). The authors conducted a study analyzing an interview on the use of AI in medical practice. According to this study, ChatGPT demonstrates a significant ability to identify descriptive themes in qualitative data. It was also able to provide more nuanced analyses. However, according to the authors, human supervision would be necessary to guarantee the precision of the analysis, particularly to prevent misinterpretations or decontextualized interpretations. Similarly, Sen et al. (2023) demonstrated that ChatGPT had the ability to create codes, categories and themes from qualitative data, while directly quoting relevant text passages (5). Artificial Intelligence would also be able to interpret the meaning of the data and analyze the relationships between words.

Since qualitative research involves reducing data into codes and categories to facilitate synthesis and interpretation (6), AI could serve as a valuable tool for generating codes (7), provided that queries and parameters are carefully controlled to align with the specific focus of the research (8). 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 (9). Contributions from qualitative research (3, 10) 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 (11-12). 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 the creation of causal link diagrams (13). 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 (14). 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 (15-16). One of the limitations of Artificial Intelligence is its inability to generate emotion (17), so the question that naturally comes to mind is its ability to perceive, name and even measure emotions. Our search question will be written as follows.

Do Artificial Intelligences systems facilitate the reliable identification of emotional patterns in written texts, whatever AI model used?

In our opinion, this research question is particularly relevant given that previous research has generally only considered a single Artificial Intelligence, without considering the possible variation in results depending on Artificial Intelligence.

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

As previously described in the second paper, 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 (18-21). However, as noted by Dorn and Sengmueller (2009), students who are not directly motivated by the financial value of portfolios could overtrade (22). 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 (23-24). However, when the articles mentioned were written, Artificial Intelligence had not yet become a reality and therefore all the data had been encoded manually.

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 (25). 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 (26). 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 (27). Under the influence of behavioral finance and better control of some technological tools, research methods have tended to shift (28). Bloomfield and Anderson (2009) also argue that experimentation is underused in the financial field but would be useful for testing behavioral finance and biases (29).

For answering our research question, we will focus on documents 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 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. In an effort to improve our perception of the emotional charges in the documents (compared to what was achieved in the second paper), we applied a series of six queries. The first (corresponding to what we did previously) covers eight emotions taken from the selected classification (anger, anticipation, disgust, fear, happiness, sadness, surprise and optimism). Then, in the second query, we subdivide anticipation and surprise into two parts (positive and negative) in order to achieve greater precision. In the previous article, these two emotions were considered neutrally because, theoretically, they could have both a negative and a positive connotation. By proceeding on this basis, we can produce a more precise view of the emotional fields under analysis. The third presented the general context in which the written documents were collected (three days of continuous trading), the fourth provided details on the work environment (a slight negative stock market context), the fifth considered the gender of the writer (male or female). The last query specifies that a reward of 200 euros was offered for the portfolio with the highest financial performance. Through this approach, we are following the recommendations provided by Zhang et al., 2024 (16).

Bibliographical references will mainly be mentioned as the queries are being presented.

Queries were structured as follows:

Query 0: I am going to give you a text and ask you to identify emotions that the text brings out; it is a written text.

This query, which does not expect a structured response from the Artificial Intelligences, aims to clarify the context that will determine the choice of following queries.

Query 1: text + for the analysis of emotions, I want you to take into consideration the following emotions: anger, anticipation, disgust, fear, happiness, sadness, surprise, optimism. give me a summary table of the percentages and make sure that the total equals one

Through this query, we try to identify all the emotional forces in the written document (positive, neutral – namely anticipation and surprise - and negative). Let's remind that, compared to the initial classification of Harmon-Jones et al. (2016), we have replaced confidence with optimism because confidence could be understood by Artificial Intelligences as a positive emotion (overconfidence) or a negative emotion (lack of confidence) (30). 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.

Query 2: same work, same text but using the following emotions: anger, positive anticipation, negative anticipation, disgust, fear, happiness, sadness, positive surprise, negative surprise, optimism. Give me a summary table of the percentages and make sure that the total equals one.

Through this query, we wish to achieve greater precision regarding the emotions taken into consideration, by considering only two polarities (positive or negative). In the initial typology, anticipation and surprise were considered neutrally (because both polarities were theoretically possible), which could have led to confusing results. However, this method allows us to get a clearer picture of the emotional charges that have been identified.

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 four 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. Finally, we will take into consideration that a reward was offered for the highest financial portfolio at the end of the experiment (200 euros).

Query 3: 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, emotions act as decision-making

vectors and influence how people assess risky situations (31-33). In addition, emotions affect the perception of gains and losses, as well as the behaviors associated with financial results (34). Grimani et al. (2022) show that individuals are more inclined to take risks when facing choices involving losses, which highlights the importance of the fear of loss in the decision-making process and, more generally, the importance of emotions in behavioral theory (35). Their study reinforces the idea that emotions, particularly those related to the anticipation of losses, are essential to understanding economic behavior and decision-making. Shafqat (2024) also emphasizes that individual investors will be more influenced by emotional biases than institutional investors (36). Thus, the frequency of transactions by individual investors would increase with the intensification of emotional biases, while institutional investors would show a less significant association. The results indicate that emotional biases have a negative impact on the decision-making and performance of individual investors, while for institutional investors, this impact is generally insignificant. The study carried out by Morewedge & Buechel (2013) highlights the importance of recognizing the differences between affective forecasts and real experiences, as well as the need for a more precise evaluation of the influences of probability specifications on emotional responses (37). By insisting on the duration of the experience in the prompt, 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 4: 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.

As presented in the first two articles, 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 (38), 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 (39).

Query 5: 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 (40-42).

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 (43). 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 (44). This difference could be explained as men are more likely to overestimate their knowledge and therefore be affected by overconfidence and optimism (45).

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 (46). 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 (47). 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. Contrary to popular belief, Osmani and Doda (2025) show that, in a managerial context, there are no significant differences between men and women in terms of risk-taking behavior (48). This calls into question the idea that women are systematically more cautious than men. Although women tend to prefer more predictable outcomes, this does not translate into risk aversion in the context of strategic decision-making. The study suggests that the perception that women are more risk-averse could be based on generalizations and gender stereotypes, rather than on real differences in risk-taking behavior.

Query 6: same context for the written passage, same male author who wrote the text, and consider that a reward of 200 euros was provided for the highest financial portfolio, and the sum of the percentages must equal 1. Basically, the reward is intended to encourage students to behave like professional traders (49).

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 reasons explaining the changes are given below for one participant, Artificial Intelligence per Artificial Intelligence. All comments in italics come directly from what was generated by the three Artificial Intelligences. It should be noted that the length of the comments provided can vary more or less substantially from one Artificial Intelligence to another.



ChatGPT Adjustments

Query 0

Sounds good! Go ahead and share the text whenever you're ready, and I'll help you identify the emotions it evokes.

Query 0 to 1: not applicable, already addressed in the second article

Query 1 to 2

- Fear: dominant throughout the experience, related to market uncertainty and the fear of making bad choices.
- Optimism: visible at the end of the text, driven by an acceptance of losses and a desire to succeed.
- Negative anticipation: expressed by pessimistic expectations about investments, driven by doubt and inexperience.
- Positive anticipation: related to decisions taken with hope, despite the risks.
- Sadness: present in financial losses and the feeling of not being up to the task.
- Anger: experienced in regret and frustration at missed opportunities.
- Disgust: more discreet, turned inwards in moments of dissatisfaction or unfavorable comparison.
- Negative surprise: caused by unexpected market reversals.
- Positive surprise: perceived in certain reassuring exchanges or unexpected increases.
- Negative surprise: caused by unexpected market reversals.
- Positive surprise: perceived in certain reassuring exchanges or unexpected increases.
- Happiness: very briefly, but present in moments of improvement or understanding.

Query 2 to 3

Excellent, with the clarification that the text is based on a three-day stock market experience, the changing nature of the experience is better considered: the progression of the emotional state day after day, between hope, uncertainty, regret and learning. This breakdown reflects the short duration of the experience, where strong and changing emotions follow each other in quick succession, including fear and frustration, but also a few moments of optimism towards the end.

Query 3 to 4

With this additional clarification - a three-day stock market experience in a slightly negative context - the overall emotional intensity is a little more moderate: less panic or sudden fall, but still uncertainty, doubt, some regrets, and sometimes disappointed expectations.

Query 4 to 5

The fact that the text was written by a male student does not radically alter the emotional analysis, but it may slightly affect the wording of the feelings: sometimes there is a tendency to retain certain emotions such as sadness or fear, or to express them in a more factual or detached style. A form of pragmatic resilience can also be observed towards the end of the text.



Query 5 to 6

The financial reward (€200) for the best portfolio is a subtle change to the emotional dynamic. It introduces additional pressure, a concrete objective, and therefore an increase in anticipation (both positive and negative), underlying stress, and potentially more frustration in the case of losses or underperformance. There is also an underlying competitive motivation. Anticipation (both positive and negative) takes on a more central role.

Gemini Adjustments

Query 1 to 2

Justification of this new distribution (with reference to your extended classification):

- Fear (25%): As in the previous analysis, fear that the situation will worsen and uncertainty about the decision to sell or to wait are interpreted as fear. The feeling of inferiority also contributes to this category.
- Sadness (20%): Regret at not having sold at the top and the financial loss are associated with sadness. The resigned acceptance of an unfavorable situation is also interpreted here as a form of sadness.
- Negative anticipation (15%): The anxious wait to see if the situation would get worse after the Schneider purchase (“I feared that the situation would worsen”) is clearly a negative anticipation.
- Optimism (10%): The idea of having reached rock bottom (“I thought I had reached rock bottom”) is a form of optimism about future improvement.
- Anger (10%): Frustration at the unfavorable development of LVMH (“which annoyed me at first”) is still categorized as anger.
- Negative surprise (10%): The difficulty in getting used to the interface at the beginning of the experiment (“it was difficult for me to get used to the interface”) is interpreted as a negative surprise in the face of unexpected complexity. The realization that the increase on the last day did not cover the purchase price is also a negative surprise.
- Positive anticipation (5%): The wish that LVMH's positive performance will continue for the other investments (“I wanted it to continue for the other investments”) is a form of positive anticipation.
- Disgust (5%): The feeling of being “in a position of inferiority” could be associated with a slight feeling of disgust towards this situation.
- Happiness (0%) and positive surprise (0%): There is no explicit mention in the text of happiness or positive surprise. Relief at the end is not categorized as happiness and is not a positive surprise in itself.

This breakdown is based on an interpretation of your text through the emotions you specified. Adding nuances to the categories of surprise and anticipation allows for a more detailed analysis according to your classification.



Query 2 to 3

Justification for this new distribution, taking into account the context of the three-day stock market experience:

- Fear (20%): Fear remains prevalent in the context of potential losses and market uncertainty, especially at the beginning of the experience when adjustment is difficult. However, given that the experiment is limited to three days, a certain degree of urgency and increased focus on the short term could slightly reduce overall fear compared to a longer experiment.
- Sadness (18%): Regret at the financial loss and the missed opportunity remains strong. The short-term nature of the experiment could intensify the feeling of loss, as there is less time to recover.
- Negative anticipation (15%): The concern that the situation will worsen remains significant, especially with the volatility of the market over a short period.
- Optimism (12%): There is hope for a rebound, even a late one, especially with the mention of a rise on the last day. The short nature of the experience could encourage optimism to be more focused on short-term opportunities.
- Anger (10%): Frustration with adverse market movements and feelings of inexperience remain present.
- Negative surprise (8%): Initial difficulty in adapting and disappointment at not covering the purchase price at the end are negative surprises in the context of this short experience.
- Positive anticipation (7%): The hope of understanding the market and seeing the investments perform positively, even briefly, is a positive anticipation.
- Disgust (5%): The feeling of inferiority and potentially frustration with one's own inexperience can generate a slight disgust.
- Happiness (3%): The relief at the end of the experience and the satisfaction of seeing a shared strategy work for some colleagues could induce a slight feeling of happiness or satisfaction.
- Positive surprise (2%): The unexpected rise on the last day, even if insufficient, is a small positive surprise.

The time frame of the three-day stock market experience slightly influences the weighting of emotions. The short-term focus can amplify certain emotions (such as sadness in the face of a rapid loss) and potentially moderate others (such as a more diffuse fear in the long term). Rapid learning and fluctuations concentrated over a short period of time can also influence feelings of surprise and anticipation.

Query 3 to 4

Justification for this new distribution, taking into account a slightly negative stock market context:

- Sadness (22%): In a slightly negative context, regret at even a moderate loss can be amplified because one might expect better results or stagnation. Disappointment at not having been able to negotiate even a slightly bearish market can reinforce the sadness.
- Fear (18%): Although the market is not in crisis, the fear of further losses and of not understanding the dynamics, even in a slightly negative context, remains present, especially for a novice.

- Negative anticipation (16%): The concern that the slight negative trend will worsen, especially over a short period such as three days, can be more pronounced. The fear of seeing one's investments continue to fall, even slightly, is real.
- Optimism (10%): The hope of a turnaround remains present, but it could be slightly tempered by the reality of a market that is generally on the decline, even slightly.
- Anger (9%): The frustration at losses and the feeling of not being able to do anything about it may be slightly mitigated by the fact that the overall market is not in free fall, but it is still an emotion that is present.
- Negative surprise (8%): The initial difficulty in adapting and the realization that even a slightly negative market can lead to losses can be perceived as negative surprises.
- Positive anticipation (7%): The hope of understanding and taking advantage of opportunities, even in a slightly bearish market (for example, buying low in anticipation of a rebound), persists.
- Disgust (5%): The feeling of inferiority in the face of a market that, even if only slightly negative, seems difficult to control, may remain.
- Happiness (3%): The relief at the end of the experience and the satisfaction of having potentially limited losses in a negative context could induce a slight feeling of happiness.
- Positive surprise (2%): A slight unexpected rise, even in a globally negative context, can generate a small positive surprise.

The news of a slightly negative stock market shifts the balance of emotions slightly. Sadness and negative anticipation could be slightly more pronounced because of the disappointment of not performing positively even in such a context, while fear could be slightly tempered by the absence of a major crisis.

Query 4 to 5:

Justification for this new distribution, taking into account the male gender of the author (student) in a slightly negative stock market context:

It is crucial to note that generalizing emotions according to gender is a simplification and can be stereotypical. However, based on observed trends (which are not absolute) and remaining cautious, the percentages could be slightly adjusted as follows:

- Sadness (21%): Sadness about loss and regret remains significant. Students may feel increased pressure related to performance and success, which could intensify sadness about a negative result, even in a mildly bearish market.
- Fear (17%): The fear of failure, of not understanding and of losing money remains present. For a student, financial resources may be more limited, which makes the loss potentially more impactful.
- Negative anticipation (16%): The concern about a possible worsening of the situation remains strong, especially with the pressure to succeed in this experience.

- Anger (11%): A slight increase in anger or frustration could be observed, potentially related to a feeling of inefficiency or of not being up to the task, especially in a context where the market is not in a major crisis.
- Optimism (10%): The hope of a rebound and of understanding the market remains, but could be slightly tempered by the frustration of the initial results.
- Negative surprise (8%): The difficulty of adaptation and the disappointment of losses, even small ones, remain negative surprises.
- Positive anticipation (7%): The hope of learning and succeeding in the future persists.
- Disgust (5%): The feeling of inferiority or incompetence in the face of the market could be slightly more pronounced in an inexperienced student.
- Happiness (3%): Relief that the experience is over remains a minor source of joy.
- Positive surprise (2%): A slight unexpected increase can always occur.

Important: These adjustments are based on conservative generalizations and should not be interpreted as absolute truths about male emotions. Emotional experiences are deeply individual. The objective here is to respond to your request by integrating the new parameter of the author's gender while recognizing the limits of such generalizations.

Query 5 to 6:

The inclusion of a reward for the highest portfolio introduces an additional element of competition and challenge, which may slightly alter the balance of emotions:

- Fear (20%): The fear of losing money is always present, but it may be slightly intensified by the prospect of not winning the reward. The fear of failure in a competitive context may be stronger.
- Sadness (19%): The regret at the initial financial loss is still there, but it can be amplified by the disappointment of moving away from the possibility of winning the reward.
- Negative anticipation (15%): The worry that the situation will get worse is still present, with the additional consequence of reducing the chances of winning the reward.
- Anger (12%): Frustration and exasperation at losses and feelings of inefficiency may be slightly increased by the feeling of losing an opportunity to win.
- Optimism (11%): The hope of a recovery and of still being able to compete for the reward may be slightly stronger, potentially motivating greater risk-taking.
- Negative surprise (8%): Initial difficulty in adapting and disappointment at losses remain negative surprises.
- Positive anticipation (7%): The hope of understanding the market and making gains to aim for the reward is present.
- Disgust (4%): The feeling of inferiority could be slightly mitigated by the motivation of the competition.

- Happiness (3%): The feeling of relief at the end of the experience remains, and there may be slight satisfaction having taken part in the competition.
- Positive surprise (1%): An unexpected increase that brings the reward closer could generate a small positive surprise, although the overall situation described in the text does not favor it very much.

The existence of a reward tends to polarize emotions slightly, potentially intensifying the fear of failure and the sadness of loss, while stimulating a certain level of optimism and competitive motivation (which can also result in frustration if the objectives are not achieved).

DeepSeek Adjustments

Query 1 to 2

Adjusted distribution:

- Negative anticipation (12%) and fear (14%) dominate due to uncertainties and fears related to bad decisions.
- Sadness (18%) remains high due to regrets and losses.
- Optimism (12%) and positive anticipation (10%) reflect the hope of recovery.
- Surprises (positive/negative) and happiness are more occasional.

Query 2 to 3

Justification of the adjustments:

- Increase in negative anticipation (17%) and fear (15%) to reflect the permanent uncertainty of trading over 3 days
- Optimism maintained at 12% because it was present at the end of the experiment
- Reduction in happiness (6%) and positive surprise (4%) because gains were limited
- Negative surprise at 7% for movements that are contrary to expectations
- Anger and disgust at 8% and 7% respectively for occasional frustrations

This breakdown better captures the stress and emotional swings of a short and intense stock market experience.

Query 3 to 4

Key adjustments:

- Significant increase in negative anticipation (20%) and fear (18%) to reflect the difficult market context
- Sadness increased to 16% for losses incurred
- Reduction in optimism (10%) and positive anticipation (8%) in this unfavorable climate
- Negative surprise at 9% (more volatile market than expected)
- Minimization of positive emotions (happiness 4%, positive surprise 2%)
- No change in anger (7%) and disgust (6%) for the frustrations felt

This breakdown clearly highlights the psychological impact of a slightly falling market on a novice trader, with a clear dominance of negative emotions (80% in total) while retaining a degree of realistic optimism.

Query 4 to 5

Changes made to reflect the male profile:

- Slight increase in anger (+3%) and reduction in fear (-2%) according to trends observed in studies on gendered emotional expression
- Optimism maintained at a relatively high level (12%) - studies show that men tend to maintain strategic optimism in situations of failure
- Rebalancing between negative (19%) and positive (9%) anticipation - reflecting a more offensive approach despite the negative context
- Slight increase in active emotions (anger, optimism) at the expense of passive emotions (fear, sadness)

This distribution maintains the predominantly negative stock market context (70% negative emotions) while incorporating the behavioral nuances typical of male profiles in trading situations.

Query 5 to 6

Key adjustments:

- Increase in negative anticipation (21%): increased pressure due to the financial stakes
- Increased optimism (15%): motivation through potential reward
- Increased fear (17%): fear of losing earning opportunities
- Reduction in disgust (3%): the financial reward mitigates feelings of personal failure
- Anger maintained (11%): frustration at missed opportunities
- Reduced positive surprises (1%): in a generally negative market

This breakdown reflects:

- The motivational impact of reward (optimism +15%)
- Increased competitive pressure (negative anticipation +21%)
- The risk/reward dynamic typical of male behavior in finance
- Maintaining a negative emotional base (68%) consistent with the market

Before going into the results, some comments should be made on the data processing by the Artificial Intelligences. For all queries, 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 emotional 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. It should be noted that, in some cases, the same percentages are observed, and the emotions are then ranked at the same level and separated by the “/” sign.

Table 3. Overview of the Emotional Combinations according to the Selected Query

1	Q1	Q2	Q3	Q4	Q5	Q6
GPT¹	Sadness, Fear	Sadness, Fear/Negative Anticipation	Negative Anticipation, Sadness	Negative Anticipation, Sadness	Negative Anticipation, Sadness	Negative Anticipation, Sadness
GEM²	Fear, Sadness	Fear, Sadness	Fear, Sadness	Sadness, Fear	Sadness, Fear	Fear, Sadness
DS³	Sadness, Fear/Anticipation/Optimism	Sadness, Fear	Negative Anticipation, Fear	Negative Anticipation, Fear	Negative Anticipation, Fear	Negative Anticipation, Fear
2	Q1	Q2	Q3	Q4	Q5	Q6
GPT	Sadness, Fear	Sadness, Negative Anticipation	Sadness, Negative Anticipation	Sadness, Negative Anticipation/Positive Anticipation	Sadness, Positive Anticipation	Sadness, Positive Anticipation
GEM	Sadness, Surprise	Sadness, Negative Surprise	Sadness, Negative Surprise	Sadness, Negative Surprise	Sadness, Negative Surprise	Negative Surprise, Sadness
DS	Sadness, Fear	Sadness/Fear, Negative Surprise	Sadness, Fear	Sadness, Fear	Sadness, Fear	Positive Anticipation, Anger
3	Q1	Q2	Q3	Q4	Q5	Q6
GPT	Happiness, Disgust	Negative Anticipation, Positive Anticipation	Negative Anticipation, Happiness	Negative Anticipation, Happiness	Negative Anticipation, Happiness	Happiness/Negative Anticipation, Positive Anticipation
GEM	Sadness/Optimism, Disgust	Optimism, Sadness/Disgust	Optimism, Sadness	Sadness, Optimism	Sadness, Optimism	Sadness, Optimism/Happiness
DS	Optimism, Disgust	Optimism, Disgust	Negative Anticipation, Disgust	Negative Anticipation, Disgust	Negative Anticipation, Disgust	Optimism, Negative Anticipation

¹ ChatGPT

² Gemini

³ DeepSeek

					Optimism	
4	Q1	Q2	Q3	Q4	Q5	Q6
GPT	Disgust, Sadness	Disgust, Sadness	Disgust, Negative Anticipation	Disgust, Negative Anticipation	Disgust, Negative Anticipation	Disgust, Negative Anticipation
GEM	Surprise/Sadness, Disgust	Negative Surprise, Disgust	Negative Surprise, Disgust	Negative Surprise, Disgust	Negative Surprise, Disgust	Negative Surprise, Fear
DS	Disgust, Anticipation	Disgust, Fear	Negative Anticipation, Disgust	Negative Anticipation, Disgust	Negative Anticipation, Disgust	Negative Anticipation, Optimism
5	Q1	Q2	Q3	Q4	Q5	Q6
GPT	Sadness, Happiness	Sadness, Negative Anticipation	Negative Anticipation, Sadness	Negative Anticipation, Sadness	Negative Anticipation, Sadness	Negative Anticipation, Positive Anticipation
GEM	Sadness, Optimism	Sadness, Optimism	Sadness, Optimism/Fear/Happiness	Sadness/Negative Anticipation, Optimism/Fear	Negative Anticipation, Sadness	Negative Anticipation, Fear
DS	Fear, Happiness	Sadness, Fear	Sadness, Fear	Sadness, Optimism	Optimism, Positive Anticipation	Optimism, Positive Anticipation
6	Q1	Q2	Q3	Q4	Q5	Q6
GPT	Fear, Surprise	Fear, Sadness/Negative Anticipation	Fear, Negative Anticipation	Fear, Sadness/Negative Anticipation	Fear, Sadness	Fear, Sadness
GEM	Surprise, Sadness	Negative Surprise, Sadness	Negative Surprise, Sadness	Negative Surprise, Fear	Negative Surprise, Fear	Negative Anticipation, Fear
DS	Fear, Sadness	Negative Surprise, Fear	Negative Surprise, Fear	Negative Surprise, Fear	Negative Surprise, Fear	Negative Surprise, Fear
7	Q1	Q2	Q3	Q4	Q5	Q6
GPT	Sadness, Anticipation	Fear, Sadness/Negative Anticipation	Negative Anticipation, Fear	Negative Anticipation/Sadness, Fear	Negative Anticipation	Negative Anticipation, Sadness

					ion, Sadness	
GEM	Sadness, Anticipation	Sadness, Negative Anticipation	Sadness, Negative Anticipation	Sadness, Negative Anticipation	Sadness, Negative Anticipation	Sadness, Negative Anticipation
DS	Sadness, Fear	Sadness, Fear	Sadness, Fear	Sadness, Fear	Sadness, Fear	Sadness, Fear
8	Q1	Q2	Q3	Q4	Q5	Q6
GPT	Anticipation/Happiness, Fear/Sadness	Negative Anticipation, Happiness	Negative Anticipation, Happiness	Negative Anticipation, Happiness	Negative Anticipation, Happiness	Negative Anticipation, Happiness
GEM	Sadness, Anticipation	Sadness, Negative Anticipation	Sadness, Negative Anticipation	Negative Anticipation, Sadness	Negative Anticipation, Sadness	Negative Anticipation, Sadness
DS	Anticipation/Optimism, Anger/Happiness	Positive Anticipation/Optimism, Anger	Positive Anticipation, Anger	Positive Anticipation, Anger	Anger, Positive Anticipation	Anger, Positive Anticipation

For the three Artificial Intelligences selected, a large number of negative emotions were detected (except for case 8, DeepSeek processing). Unsurprisingly, given the context under analysis, we observe a large under-representation of positive emotions. In the large majority of cases (only case 8 with DeepSeek processing does not correspond to the conclusion), the neutral version of anticipation identified in the first query is transformed into negative anticipation in the following query and both negative and positive in the next queries. For Query 2, this result could be compared with the theory of regret, in other words that investors do not make any choices so as not to have to endure regret. In all cases, the surprise considered neutral in the first query is identified as a negative surprise (a bad surprise) in the following queries. These results therefore provide a more refined analytical perspective and give Artificial Intelligence the ability to generate data that is more in line with the emotional reality of the participants. Considering the results based on surprise and anticipation as non-divisible emotions, between the lines it could be read that negative charges must be very present in each of these emotions (see paper 2). The addition of the query in this part of the research reinforces the robustness of our results.

Emotions polarities were defined as follows:

Table 4. Definition of Emotional Polarity.

Emotions	Polarity
Optimism	Positive (+)
Happiness	Positive (+)
Anticipation (Q1)	Neutral
Positive Anticipation	Positive (+)
Negative Anticipation	Negative (-)
Surprise (Q1)	Neutral
Positive Surprise	Positive (+)
Negative Surprise	Negative (--)
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. As it was the case for the second part of our research, our results demonstrate a (very) 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. According to this first result, we will now turn to emotional polarities in couples.

Table 5. Overview of the Emotional Combinations according to the Selected Query Based on Emotional Polarity.

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



4	Q1	Q2	Q3	Q4	Q5	Q6
GPT	(-, -)	(-, -)	(-, -)	(-, -)	(-, -)	(-, -)
GEM	(Neutral/-, -)	(-, -)	(-, -)	(-, -)	(-, -)	(-, -)
DS	(-, Neutral)	(-, -)	(-, -)	(-, -)	(-, -)	(-, +)
5	Q1	Q2	Q3	Q4	Q5	Q6
GPT	(-, +)	(-, -)	(-, -)	(-, -)	(-, -)	(-, +)
GEM	(-, +)	(-, +)	(-, +/-)	(-/+, +/-)	(-, -)	(-, -)
DS	(-, +)	(-, -)	(-, -)	(-, +)	(+, +)	(+, +)
6	Q1	Q2	Q3	Q4	Q5	Q6
GPT	(-, Neutral)	(-, -/-)	(-, -)	(-, -/-)	(-, -)	(-, -)
GEM	(Neutral, -)	(-, -)	(-, -)	(-, -)	(-, -)	(-, -)
DS	(-, -)	(-, -)	(-, -)	(-, -)	(-, -)	(-, -)
7	Q1	Q2	Q3	Q4	Q5	Q6
GPT	(-, Neutral)	(-, -/-)	(-, -)	(-/-, -)	(-, -)	(-, -)
GEM	(-, Neutral)	(-, -)	(-, -)	(-, -)	(-, -)	(-, -)
DS	(-, -)	(-, -)	(-, -)	(-, -)	(-, -)	(-, -)
8	Q1	Q2	Q3	Q4	Q5	Q6
GPT	(Neutral/+, -/-)	(-, +)	(-, +)	(-, +)	(-, +)	(-, +)
GEM	(-, Neutral)	(-, -)	(-, -)	(-, -)	(-, -)	(-, -)
DS	(Neutral/+, -/+)	(+/+, -)	(+, -)	(+, -)	(-, +)	(-, +)

By considering the emotional polarities inside the combinations, on the one hand, the results remain relatively stable from one query to another for Gemini, and the negative emotional trend is consolidated as the queries are submitted. On the other hand, for DeepSeek, the introduction of the query relating (Query 5) to the person's gender and the fact that a reward was given at the end of the experiment (Query 6) reveal more positive emotional etiquettes (optimism and positive anticipation). The same kind of results are found for ChatGPT, although to a lesser extent. The two queries (Q5 and Q6) did not, however, modify the results generated by Gemini. The overall impression is that as more queries are added, the results become less and less homogeneous from one Artificial Intelligence to another and, depending on the Artificial Intelligence selected, the emotional profiles can diverge greatly, in particular after considering the last query. As we have previously shown, Artificial Intelligences can highlight a general emotional context (in our case, negative), but seems less reliable in how it consistently identifies more nuanced emotional details. The use of additional queries seems to change how Artificial Intelligences process the data to generate results and seems to result in a deterioration of the homogeneity of the results. For this purpose, the question is to know when to stop submitting new queries. Another solution would be to work on the basis of results generated by a single Artificial Intelligence, but then doubts could be raised about their ability to be replicated and their scientific robustness.

Table 6. Overview of the General Emotional Trend for All Queries

Emotion	Query 1	Query 2	Query 3	Query 4	Query 5	Query 6	Total	Percentage
Anger	1	1	1	1	1	2	7	0,0225
Anticipation	7	0	0	0	0	0	7	0,0225
Positive Anticipation	0	1	1	3	3	6	14	0,045
Negative Anticipation	0	9	13	14	12	13	61	0,196
Disgust	6	5	4	4	3	1	23	0,074
Fear	10	10	9	9	7	8	53	0,17
Happiness	5	1	3	2	2	3	16	0,051
Sadness	18	17	13	14	13	10	85	0,273
Surprise	4	0	0	0	0	0	4	0,013
Positive Surprise	0	0	0	0	0	0	0	0
Negative Surprise	0	5	4	4	4	3	20	0,0643
Optimism	5	4	2	3	3	4	21	0,0675
Total	56	53	50	54	48	50	311	1

From our results, considering all the emotions identified by the Artificial Intelligences (all queries), it appears that the three most significant emotional charges are sadness, negative anticipation (including anticipation from Query 1) and fear, which confirms the negative emotional climate resulting from the experience. Our results also show that the positive surprise never occurred in any emotional couple. We also observe that positive anticipation becomes a much more present emotion in couples when the query regarding the offer of a reward is added at the end of the experiment. In any case, the fact that the anticipation was split into two polarities seems to have provided a better picture of the emotional climate of the experience (in contrast to surprise).

Table 7. Summary of the Emotional Polarity (all AI).

Emotion Polarity	Positive Emotions	Negative Emotions
Percentage	0,164	0,836

From the analysis of all the queries taken together, our results reveal that 83,6 % of the emotions expressed have negative charges (whatever the position in the combination), and 16,4 % of the emotions are considered positive. This result suggests a strong 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. However, the result achieved for positive polarity is significantly higher

than from the second study, in which only 3% of emotions had a positive charge. This can be explained by the positive anticipation that seems to arise after the fourth query.

Table 8. Changes in Emotional Polarities in Response to the Queries (All AI).

Emotion Polarity (%)	Query 1	Query 2	Query 3	Query 4	Query 5	Query 6
Positive Emotions	0,179	0,113	0,120	0,148	0,167	0,260
Neutral Emotions (Q1)	0,196	0,000	0,000	0,000	0,000	0,000
Negative Emotions	0,625	0,887	0,880	0,852	0,833	0,740
Total	1	1	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 between Query 1 and Query 2. This can be due to the inclusion of negative anticipation as a negative emotion in Query 2. In Query 1, the anticipation was considered neutral. From Query 3 and the mention of the stock market context for the experiment, the percentage of positive emotions increases. The strongest increase is noted between the fifth and sixth queries, when it is specified that a reward would be offered to the highest financial portfolio. It therefore seems, in the “mind” of the Artificial Intelligences (and more specifically DeepSeek), that a reward would positively reinforce the emotional climate: even if the stock market climate is negative, it is conceivable that the participants would anticipate positive results based on the hope of winning the prize. As previously mentioned, the problem comes from the high concentration of positive emotions generated by DeepSeek and not necessarily by other Artificial Intelligences. On this basis, it is therefore difficult to conclude that the incentive had any effect on the emotional charges produced.

In response to how the different queries introduced have improved the understanding of the emotional climate, we will answer very cautiously. The addition of new queries provided a better understanding of some emotional realities (particularly in terms of anticipation) and reinforced the picture of a negative emotional climate during the experiment. On the other hand, and even if the results are not consistent from one Artificial Intelligence to another, positive emotional components clearly appear when it comes to a reward. This result mitigates the conclusion of an invariably negative emotional climate throughout the experiment.

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 (50), 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 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 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, see Lee et al., 2024) (51) 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 (52) and their personal emotional positioning (53). In the case of this study, the findings are particularly striking because the results generated by DeepSeek reveal positive emotional dynamics that do not correspond to the general negative trend identified by ChatGPT and Gemini.

5. Limitations and Additional Research Avenues

Our results are based on a small number of written documents, drafted in a specific decision-making context; 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. But this result remains disturbing considering that the documents were written in similar contexts, by people with very similar socio-demographic data. Looking at the reasons for the adjustments from one query to the next, the artificial intelligence's format of presentation seems scientifically proven, but in fact, no details are really provided about the scientific fields actually being used. Indeed, our results show that the treatments of queries can differ greatly from one Artificial Intelligence to another. Our proposal is to provide Artificial Intelligences with the scientific fields of analysis that facilitate adjustments between the queries. For example, when gender is integrated into one of the queries, it would involve providing a list of major scientific references in the field of differentiated decision-making behavior based on gender, and asking the Artificial Intelligence to refer to it to adjust the generated results. This process would give scientific consistency to the analysis

carried out by Artificial Intelligences or at least would help maintain scientific control of the process, with the limitation that the interpretation of scientific articles could differ from one Artificial Intelligence to another. Our next works will focus on highlighting emotional charges from written transcripts of semi structured interviews, and we will rely on what was suggested just before, namely that we – ourselves - define the scientific fields selected for adjustments from one query to the next.

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Appendices

Table 9. 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 10. 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 11. 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