Emotional Reactions as a Predictor of Investment Decisions
How Financial Knowledge Impacts the Role of Emotions During Investment Decisions

Elias MOSER, 11703385
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Supervisor:
Univ.-Prof. Dr. Johann Füller
Innovation & Entrepreneurship
Institut for Strategic Management, Marketing und Tourism
ABSTRACT

Emotions play a crucial role in human decision-making. However, the research area of emotions in decision-making, particularly in investment situations, has only recently started to gain relevance. An enhanced understanding of emotions in these contexts could potentially reshape our perception of financial behaviour, leading to more accurate predictions. This thesis addresses this gap by exploring the influence of desire, anger, and core affect on investment decisions, and how financial literacy affects the relationship between these factors in a crowdfunding context. This study aims to answer the following questions in the context of crowdfunding: How does financial literacy moderate the influence of emotions on investment decisions, and how does the funding status influence investment behaviour? An experimental approach was used in the study, with data collected through affective computing and questionnaires. The findings of this study indicate that desire positively impacts investment decisions, while anger has a negative influence. However, no moderating effect of financial literacy on the influence of emotions in investment decisions was detected. Additionally, the funding status significantly impacts investment decisions and amounts in both directions. A high funding status leads to more investments and greater invested sums, whereas a low funding status has the opposite effect. This thesis provides new insights into the role of emotions in investment decisions, as well as the role of funding status. To remain within the scope of this thesis, other characteristics that may impact investment decisions, such as idea evaluation, were considered only as control variables. Future research might account for these factors to build a more comprehensive understanding of how emotions influence investment decisions. Another avenue for future research would be to use a sampling technique that allows for generalizability as in this study the results are just representative of the sample.

Keywords: emotions, investment decision, crowdfunding, financial literacy, affective computing
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1. Introduction

1.1. Problem Statement and Research Gap

Emotions have been studied since the time of Darwin (1872), and it is now believed that emotions significantly influence human decision-making. However, it wasn't until the late twentieth century that the role of emotions in decision-making was thoroughly examined (Lerner et al. 2015). For a considerable period, it was assumed that human decision-making was confined solely to cognitive and situational constraints, disregarding the influence of emotions. As various emotion theories emerged, they attributed an increased influence of emotions on individuals' behaviour. Nevertheless, the emergence of these theories sparked debates over the definition of emotions, thereby limiting the generalizability of findings, as studies were based on different interpretations of emotions. This thesis covers the discrete emotion theory by Ekman and Friesen (1971), the dimensional emotion theory by Russell (1980), and Arnold's (1960) appraisal theory of emotions. These theories vary based on their definitions of emotion, whether they believe emotions are universal, and the number of emotional states they identify, among other characteristics.

The dimensional emotion theory suggests that emotions can be differentiated based on their valence and level of arousal (Russell 1980). However, to predict how emotions influence decision-making, it is not sufficient to differentiate solely on the basis of valence and arousal. Lerner and Keltner's (2000) appraisal-tendency framework states that two negative emotions can have different influences on decision-making. For instance, Lerner et al. (2004) found that the negative emotions of disgust and sadness affect economic decision-making differently, thus linking decision-making with discrete emotions theory. Since then, further connections between emotion theories and decision-making have been studied (e.g.: Han et al. 2007; Gneezy et al. 2014), leading to a better understanding of the human decision-making process. Despite these advancements, the full impact of emotions on decision-making is not fully understood, as research in this field is still evolving. Future discoveries will likely enhance our understanding.

Consequently, our knowledge of how emotions influence investment decisions remains limited. Emotions often steer individuals away from rational decision-making, leading to their common perception as a negative influence (Aliya and Bansal 2018). Yet, this is not always the case. For example, anger can increase investors' risk tolerance (Gambetti and Giusberti 2012), which can be beneficial under favourable market conditions (Bernaola et al. 2021).
Aside from anger, the influence of discrete emotions on investment decisions is mostly uncharted territory. This thesis aims to contribute to a better understanding by focusing on the effects of desire, anger and core affect in investment situations. Also, when an investor feels positively towards something, they tend to perceive the risk of that investment as lower than it actually is (Finucane et al. 2000). This suggests that positive feelings towards a stimulus likely lead to more investments, but this direct effect has not been studied extensively.

Literature indicates that financially literate individuals make more rational investment decisions (Baker et al. 2018) and generally manage their personal budgets more effectively (Shahrabani 2012). These characteristics suggest that financial literacy may diminish the influence of emotions on investment decisions. Additionally, financially literate individuals are less likely to let behavioural biases, such as overconfidence, affect their investment decisions (Ahmad and Ali 2020). However, there is a research gap concerning the influence of financial literacy on emotions in investment decisions. Based on existing literature, this thesis aims to answer the following research question: **How does economic knowledge impact the role of emotions in investment decisions for retail investors?** This question will be explored in the context of crowdfunding. To answer this research question, elements from psychology, behavioural finance, and innovation management are integrated.

Crowdfunding is a relatively recent avenue for businesses to raise capital non-traditionally. The first crowdfunding platform, Sellaband, was eventually overtaken by Kickstarter, which established itself as the market leader. A unique feature of crowdfunding is that it allows many small investors worldwide to collectively fund a project (Agrawal et al. 2014) without high entry barriers (Hoegen et al. 2018). If a project reaches its funding goal, the business receives the raised capital. If the funding goal is not met, all investors receive their money back (Ahlers et al. 2015). A critical component of a crowdfunding campaign is the funding status, indicating how much of the necessary capital has been raised. This status reflects how the community values a project, and some individuals allow this to influence their decisions, demonstrating a herding behaviour (Vulkan et al. 2016). To analyse the presence of herding behaviour, this thesis aims to answer a second research question: **How does the funding status impact the investment decisions of retail investors?**

This thesis seeks to expand upon existing knowledge regarding emotions in decision-making, offering novel insights into the influence of emotions on investment decisions, and the effect of financial literacy on this relationship. While there is limited understanding of both the role
of emotions in decision-making and the impact of financial literacy, this thesis contributes new perspectives to these areas. However, due to the sampling technique used, conclusions drawn from these relationships can only be applied to the sample. Future research might strive for broader generalizability. Additionally, this thesis does not examine potential external factors that could influence the relationship between emotions and decision-making. Therefore, the objective of this thesis is to enhance understanding in a relatively unexplored field of research, while simultaneously recognizing the study's limitations.

1.2. Thesis Structure
The goal of this thesis is to tackle both research questions by looking at the existing literature in areas such as emotion theory, decision-making, behavioural finance, and crowdfunding. This will involve coming up with hypotheses, analysing the results, and linking these results to the existing body of work. First, key topics like emotions, decision-making, and the combination of the two will be expanded upon, outlining the current state in these fields. As such, the next chapter will focus on the existing theories, propose new hypotheses, and mention the potential limitations of this thesis. Then, the third chapter will thoroughly explain the methods used in this thesis, putting a spotlight on the research approach used during the experiment. Next, the fourth chapter will share the results of the experiment. The collected data will first be presented using basic statistics, and then the hypotheses will be tested using statistical analysis. The fifth chapter will concentrate on the connections between the results of the statistical analysis and the existing literature. This will provide a discussion on how these results add to what is already known and might even contribute to new knowledge. Along with this, any limitations will be discussed, and ideas for future research will be suggested. To wrap things up, the final chapter of the thesis will include a brief summary of the thesis content.
2. Literature Review

2.1. Emotions

Exploring emotions has been a focus for a long time. To clarify what emotions actually mean and how they differ from similar notions, this chapter will delve into various theories and definitions. The existence of primary or base emotions will also be questioned, and other categories of emotions will be discussed.

2.1.1. Definition and Theories

One of the first publications about emotions was by Darwin (1872) where he described emotion as universal across cultures and argued, that emotions have a shared biological basis in the evolutionary history of humans and higher animals. He published those findings in his book *Expression of Emotion in Man and Animals* and influenced further research on emotion. Since then, emotions were a popular research domain in various fields but as Scherer (2005) pointed out, there is no consensus about what defines an emotion. The author views this as a major downside because as long as there is no consensus definition of emotion, generalizable research will stay difficult (Scherer 2005). In addition, a missing consensus definition of emotions leads, according to Mulligan and Scherer (2012), to too many misunderstandings and fruitless debates because two sides with different definitions cannot compare their results. Since there is no agreement among researchers on the essential nature of emotions, it is important to examine the various definitions of emotion that have been proposed. Thus, I will investigate the different interpretations of emotion that exist within the research community.

One of the first theories of emotions was proposed by James (1884) as he concluded emotions are a result of bodily changes rather than solely based on cognitive processes. Together with (Lange 1885), they put forward the James-Lange theory which claims that specific bodily responses determine the type of emotion humans feel. Thus, according to the James-Lange theory, when we encounter a stimulus, it elicits a physical reaction in our body, which in turn causes us to experience the corresponding emotion. Cannon (1927) disagreed that bodily responses are specific enough to cause a wide range of emotional experiences among other aspects and proposed the Cannon-Bard theory. The Cannon-Bard theory claims that emotional experiences are the result of the simultaneous activation of both the physiological and cognitive components of emotion (Cannon 1927). Therefore, a stimulus triggers both a physiological response and a cognitive appraisal at the same time, leading to the experience of an emotion. Schachter and Singer (1962) expanded the Cannon-Bard theory by proposing the two-factor
theory of emotion. The theory suggests that our emotional experience depends on the combination of the cognitive interpretation of the situation and the physiological response (Schachter and Singer 1962). Hence, the two-factor theory of emotions expands the Cannon-Bard theory by stressing the importance of cognitive interpretation in combination with the physiological response.

Besides competing emotion theories, different definitions of what emotions exist as well and make generalizability across definitions difficult. A widely discussed definition of emotion is Scherer’s (2005) work, where he proposes a component process definition. He states that an emotion is an episode of interrelated, synchronized changes in the states of all or most of the five organismic subsystems in response to the evaluation of an external or internal stimulus event as relevant to major concerns of the organism (Scherer 2005). Thereby, an emotion is impacted by the components of appraisal, bodily symptoms, action tendencies, facial and vocal expressions and the emotional experience (Scherer 2005). While Reisenzein (2007) is unsure what emotions truly are, he disagrees with Scherer’s (2005) component-process definition as he believes the measurement of emotions with mental-behavioural processes is unachievable and proposes that emotions are mental states. Further, he argues that an exact definition of emotion is not a prerequisite for meaningful research because the identification of the nature of emotion is already a relevant question of emotion research (Reisenzein 2007).

2.1.2. Emotion Theories
In this section, the intent is to provide a more detailed exploration of several emotion theories and their defining features. Specifically, the focus will be on three theories: the discrete emotion theory, the dimensional theory of emotion, and the appraisal theory of emotion. By comparing and contrasting these theories, the is aim to enhance our understanding of the field of emotion theory and shed light on the similarities and differences between these prominent approaches.

2.1.2.1. Discrete Emotion Theory
The discrete emotion theory is one of the main schools of thought in emotion research. It suggests that there are a limited number of basic emotions, also known as primary emotions, that are universal and biologically based. The idea originated from Darwin (1872) who believed that emotions are innate and developed over time for survival purposes. For example, over time humans were born with basic emotions like fear which they felt when a dangerous animal was in the area and helped them survive. Later, Ekman and Friesen (1971) built on this theory and
proposed that specific facial muscle patterns are universally linked to particular discrete emotions. The discrete emotion theory also argues that basic emotions are distinct from one another. Levenson (2011) argues that these differences can manifest in various ways, such as differences in behaviour, expression, physiology, and language. According to Levenson’s (2011) framework of discrete emotions, basic emotions are viewed as unique. They are consistent and remain the same across different species, periods of time, and locations.

According to Ekman (1992), a basic emotion must possess three key features: a distinct and universal signal, a distinct physiology, and a distinct set of universal signals that distinguish it from other basic emotions. Furthermore, Ekman et al. (1999) argue that basic emotions should be grouped into families or categories. Ekman and Cordaro (2011) propose that a single emotion is not a single state, but rather a family of related emotional states. Further, emotion families distinguish from one another and an emotion family consists of similar emotion themes with individual differences or variations (Ekman and Cordaro 2011). For instance, the terms anger, mad, pissed-off, and rage are all part of the basic emotion family of anger, while longing, wanting, craving, and desire to belong to the basic emotion family of desire (Harmon-Jones et al. 2016). Whereas there is some agreement among researchers on the criteria that define a basic emotion, as outlined by Ekman and Cordaro (2011), Levenson (2011), and Panksepp and Watt (2011), there is still no consensus on the number of basic emotions that exist or which emotions should be considered basic.

Figure 1: Similarities and discrepancies among basic emotions (Tracy and Randles 2011)

| Theoretically and empirically supported basic emotions according to each model |
|------------------|------------------|------------------|------------------|
| IZARD            | PANKSEPP & WATT  | LEVENSON         | EKMAN & CORDARO  |
| Happiness        | PLAY             | Enjoyment        | Happiness        |
| Sadness          | PANIC/GRIEF      | Sadness          | Sadness          |
| Fear             | FEAR             | Fear             | Fear             |
| Anger            | RAGE             | Anger            | Anger            |
| Disgust          | SEEKING          | Disgust          | Disgust          |
| Interest         | LUST             | Interest?        | Contempt         |
| Contempt?        | CARE             | Love?            | Surprise         |

The table shown in Figure 1 displays some disagreement between several Izard (2011), Panksepp and Watt (2011), Levenson (2011), and Ekman and Cordaro (2011), regarding which emotions are considered basic. Fear is the only emotion that all researchers agreed is basic and
labelled as such. *Happiness/Enjoyment/PLAY* and *Sadness/PANIC/GRIEF* are very similar to each other, as are *Anger/RAGE* (Tracy and Randles 2011). Izard (2011) and Levenson (2011) both added a question mark next to certain emotions, indicating that the basicness of those emotions has yet to be fully established but could be proven in the future. Ekman and Cordaro (2011) also acknowledge that the full list of basic emotions has not been scientifically proven and suggest that their model may include up to ten additional basic emotions in the future. According to them, emotional families like *Schadenfreude, Relief* and *Wonder* among others could be proven to be basic emotions as well (Ekman and Cordaro 2011).

Basic emotions can trigger physiological changes in the human body. For example, anger increases blood flow to the arms and hands, preparing a person for a fight (Levenson et al. 1990). In contrast, fear causes blood flow to redirect from the hands and arms to the legs and feet, preparing a person to flee (Ekman and Cordaro 2011). Thus, depending on the bodily changes of an individual, the experienced basic emotion someone feels could be able to be predicted. Besides, the impact of basic emotions on humans varies throughout different life stages. Infants and young children tend to have stronger reactions to basic emotions compared to adults due to their limited development of effective emotion control systems (Izard 2004). Izard (2011) gives the example that a mother’s smile is more likely to induce a smile in a 2-month-old infant than in an adult.

2.1.2.2. Dimensional Emotion Theory

The dimensional emotion theory proposes that emotions can be described along the two independent dimensions of valence and arousal (Russell 1980). Since the first suggestion that dimensions of emotions exist by Wundt (1897) and later by Schlosberg (1954), Russell’s research on dimensional emotion theory has been very influential in the field of emotion research. A lot of attention in dimensional emotion research has been around core affect, the structure of core affect and affective quality.
As can be seen in Figure 2 above, Russell (1980) claims that the two dimensions of emotion called the cognitive structure of affect, are pleasure-displeasure/misery and arousal-sleep. The horizontal dimension of pleasure-misery measures the valence of affect and the vertical dimension of arousal-sleepiness measures whether the arousal level is high or low. While, there are only two dimensions, the other four emotions seen in Figure 2 help define the quadrants of space (Russell 1980). Russell’s (1980) model suggests the variables diagonal to each other, like northeast and southwest, have opposing characteristics. For example, excitement is a high pleasure and high arousal and with its characteristics, it is the polar opposite of depression.

Core affect is, along with psychological construction, a key concept in dimensional emotion theory and a neurophysiological state like feeling good or bad, feeling energized or sleepy (Russell 2009). Thereby, the conscious experience of core affect is a blend of the two dimensions pleasure-displeasure and activation-deactivation (Russell 2003). A characteristic of core affect is that someone is always in some state of core affect and the state usually lasts much longer than an emotional episode which only lasts a short amount of time (Russell 2009). (Russell 2003) states that core affect can be either experienced as free-floating like the general mood of someone in a certain moment or can be attributed to some cause and begin an emotional episode.

In discrete emotion theory, the emergence of fear gets attributed to influencing the behaviour of humans in a way that prepares them to flee (Ekman and Cordaro 2011). This is a general assumption and fear is expected to produce the same reaction every time it emerges. However, dimensional emotion theory suggests that emotions are flexible and context-dependent mental states that are constructed by the brain (Barrett 2006). Therefore, in dimensional emotion
theory, the emotion of fear can have many effects and not every time fear is perceived it will be experienced with the same valence and arousal. Hence, dimensional emotion theory suggests that emotions are not fixed, predetermined categories with specific markers and also not universal, as discrete emotion theory argues (Barrett 2006). As a result, the interpretation of emotions isn’t seen as something universal and can vary between cultures and situations. For example, Americans assess emotional situations as more pleasant than East Asians due to cultural differences like the Western individualist cultural model versus the East Asian collectivist model (Mesquita and Walker 2003).

Lastly, it is important to distinguish between core affect and affective quality. Core affect is a non-reflective feeling that is a combination of the two basic dimensions of emotional experience, valence and arousal (Russell 2003). Affective quality is the specific subjective experience of a particular emotion and is the combination of core affect with cognitive, social and cultural factors (Russell 2003). Thus, the affective quality depends on how individuals interpret the perceived core affect. I believe, this is in line with the argument from (Barrett 2006) that emotions aren’t universal and depend on the culture and situation someone is in. According to Russell (2003), the core affect of people can stay unpleasant and with low arousal even when the acknowledge that a stimulus has positive affective quality. For example, a depressed person might be able to perceive the landscape as beautiful but still be unable to alter their depressed mood.

2.1.2.3. Appraisal Theory of Emotion
The last theory of emotion I will elaborate on for this master thesis is the appraisal theory of emotion. It was first proposed by Arnold (1960) that emotions depend on an individual’s appraisal and are not automatic responses to a stimulus. Appraisal theory was further developed by Lazarus (1966) and Smith and Ellsworth (1985). Appraisal theory suggests that our emotions are shaped by our interpretations and judgments of a situation, which can be quite complex and subjective (Scherer 1999). For example, if we evaluate something as beneficial to us, we might feel happy or excited. However, if we see something as something challenging or threatening, we might feel anxious or fearful. In appraisal theory exist nearly an infinite number of emotional states, compared to basic emotion theory where only a few emotional states exist (Ellsworth 2013). Thus, emotions can be more personal and unique to each individual compared to the basic emotion theory. This is because appraisal theory suggests that many different emotional states can exist, depending on how a person evaluates a situation.
In appraisal theory, the term appraisal means the process of evaluating how important something is for someone’s well-being (Moors et al. 2013). This evaluation happens in response to what is happening around us and triggers changes in our emotions. When we encounter something new or different in our environment, we shift our attention and start to feel something emotionally (Moors et al. 2013). This is in line with Ellsworth (2013) as she suggests that novelty is the first factor that leads to an emotional experience. She suggests that when we notice something new or different in our environment, our attention shifts from an unfocused background state to a more focused state (Ellsworth 2013). And it's at this point that we start to have an emotional experience. Besides, appraisal theory suggests that the initial appraisal can trigger a chain of future appraisal and emotional reactions (Lazarus 1991). Hence, in appraisal theory, there is a complex interplay between someone’s appraisals and emotions, where each can trigger the other in a cycle (Ellsworth 2013). For example, if you appraise the noise as a potential threat, then you might feel scared or anxious. But if you appraise the noise as just a harmless sound like a falling trashcan, then your emotional response most likely won’t be feeling scared or anxious. Based on your perceived feeling you likely observe different signals, for example registering quieter noises if you feel scared which you wouldn’t note if you feel excited and so on.

Furthermore, appraisal theory suggests that different people may experience different emotions in response to the same stimuli, based on their subjective cognitive evaluations of that stimuli (Moors et al. 2013). These evaluations may vary depending on factors such as novelty, goal congruence, controllability, and other appraisal variables. For instance, one person standing on a cliff at a lake may feel joy or desire, while another may feel fear, depending on their appraisals. The core set of appraisal variables that influence emotional episodes include goal relevance, goal congruence, certainty, coping potential, and agency (Moors et al. 2013).

Appraisal theory consists of two main components, primary appraisal and secondary appraisal, that play important roles in shaping emotional experiences. Primary appraisal evaluates the relevance of an event to one's well-being and consists of two subcomponents: motivational relevance and motivational congruence (Lazarus 1991). On the other hand, secondary appraisal evaluates one's coping resources and options, and it is divided into accountability, problem-focused coping potential, emotion-focused coping potential, and future expectancy (Lazarus 1991). According to Lazarus (1991), if a situation is deemed relevant to one's well-being, secondary appraisal becomes more crucial, as coping with the situation becomes more imperative. Primary appraisal, therefore, assesses the situation while secondary appraisal seeks
potential coping mechanisms, with the latter being greatly influenced by the outcome of the former. Smith and Ellsworth (1985) propose an alternative theory of appraisal structure in comparison to (Lazarus 1991). The authors argue that six dimensions of appraisal exist and highlight a significant relationship between one's appraisal of their circumstances and their emotional state (Smith and Ellsworth 1985). These six dimensions include pleasantness, anticipated effort, certainty, attentional activity, self-other responsibility/control, and situational control (Smith and Ellsworth 1985).

In this subchapter, the differences among various emotion theories have been outlined. Although these differences exist, thus limiting the generalizability of findings, it is still possible to simultaneously apply multiple emotion theories to measure emotions. Affective computing, which will be elaborated upon in a subsequent subchapter, exemplifies this concept by using both dimensional and discrete emotion theories concurrently. This approach will also be applied in the experiment conducted for this thesis. In my opinion, all three emotion theories furnish convincing arguments as to why their respective theory should predominate. However, none are without flaws, leaving room for other theories of emotion. For instance, the discrete emotion theory postulates that emotions are universal and homogeneous across cultures (Ekman 1992). Contrarily, the appraisal theory of emotion posits an intriguing argument, suggesting that emotions are shaped through subjective interpretation and vary across cultures (Scherer 1999). In conclusion, more research is likely required in the realm of emotion theories to establish a predominant theory. As of now, they contradict each other, making it impossible to draw a definitive conclusion.

2.2. Decision-making
This chapter aims to clarify basic principles of decision-making, taking a deeper look into certain decision theories such as the expected utility function and prospect theory, with a special emphasis on their application in investment decisions. Also, this chapter is dedicated to discussing biases that could appear during decision-making in general and particularly in investment decisions. The decision-making process in crowdfunding and crowd-investing will also be examined to identify any recurring patterns. Near the end, the chapter will highlight how financial knowledge can impact the investment decision process. Understanding the process and the theory behind decision-making is key to understanding how emotions can affect these decisions, and this chapter seeks to offer such understanding.
2.2.1. Theory and Process

First, to gain a basic understanding of decision theory, the fundamental principles will be outlined, and the factors that influence a decision will be discussed. Humans are perpetually making decisions, and there are two consistent principles about this process. First, human preferences fluctuate over time, and a viable decision theory must be capable of predicting these changes in preferences (Busemeyer and Townsend 1993). Second, the act of making a decision consumes time, and the amount of time taken can significantly influence the final choice (Busemeyer and Townsend 1993). From these observations, it can be inferred that decision-making not only requires time but is also challenging to predict because decisions can change due to shifting preferences over time. Busemeyer and Townsend (1993) found that an individual is more likely to take a risk with a decision if they make it quickly and their willingness to gamble decreases as more time is taken to reach a decision.

Decision-making, at its core, is a fundamental mental activity that happens every few seconds within the human mind, either consciously or subconsciously (Wang and Ruhe 2007). This process involves choosing a preferred option from a set of alternatives based on specific criteria (Wang and Ruhe 2007). It's widely agreed upon within decision-making theories that various aspects of an option eventually merge into one single measure to allow comparison of different options (Kable and Glimcher 2009). This is akin to comparing apples with oranges, as two distinct options are assigned a certain value, an expected return, or other categorization.

To fully grasp why a particular decision is made, it's crucial to understand the basic cognitive process. This process of decision-making can be divided into two parts, which have been labelled as System 1 and System 2 by Stanovich and West (2000). System 1's operations are typically fast, instinctive, and emotionally driven (Kahneman 2003). As such, System 1 could be viewed as the initial thought or intuition that arises when there's a shift in perception. In contrast, the operations of System 2 are generally deliberate, slower, and in some instances, governed by rules (Kahneman 2003). Hence, System 2 usually requires more time to engage and involves a cognitive process beyond just intuition, as seen in System 1. Kahneman (2003) contrasts the two systems, stating that while System 1 involuntarily generates impressions of object attributes, System 2 deliberately and explicitly produces judgments.

Decisions usually emerge from one of three scenarios. The first scenario is when the possible outcomes are known and the resulting occurrence is definite. The second scenario happens when the potential outcomes are known, along with their chances of happening. The third
scenario takes place when neither the possible outcomes nor their probabilities are known (Trommershäuser et al. 2008). Despite this distinction, forecasting a person's choice remains a challenge in either situation. This is due to the fact that even with a predictable outcome, personal preferences can shift over time and there's a potential for bias in decision-making, as pointed out by Tversky and Kahneman (1974) and further substantiated by Busemeyer and Townsend (1993). So, the subsequent subchapter will lay out different decision theories that strive to explain people's choices in scenarios of risk or uncertainty.

2.2.2. Decision Theories

Over the past century, a variety of theories regarding decisions under risk and uncertainty have emerged and developed. The expected utility theory was first proposed by von Neumann and Morgenstern (1944), and from this foundation, other theories such as prospect theory, rank-dependent theory, regret theory, and others were established (Johnson and Busemeyer 2010). The main attention will be on the expected utility theory and prospect theory. Covering all theories would go beyond the limits of this master's thesis. The aim is to explain why these two theories have been chosen and why they are the best fit for this master's thesis.

2.2.2.1. Expected Utility Theory

The earliest form of the expected utility theory was suggested by Bernoulli (1738) as a potential solution to a gambling dilemma (Starmer 2000). Building on this concept, von Neumann and Morgenstern (1944) formally introduced the expected utility theory. This theory posits that individuals choose the option with the highest anticipated result among all possibilities. Initially, their theory was confined to decisions involving options with objectively known probabilities (Johnson and Busemeyer 2010). Over time, numerous researchers have expanded on the expected utility theory. Savage (1954), for instance, incorporated subjective probabilities for certain events to account for uncertain outcomes. The premise of this theory is that individuals aim to maximise the expected value of a given quantity (Friedman and Savage 1952). Moreover, the expected utility theory operates on the assumption that individuals make choices based on rational reasoning (Johnson and Busemeyer 2010). Thus, the economic choices of all rational decision-makers should be predictable using the expected utility theory, assuming the expected utility is known.

To understand the application of the expected utility theory, consider this example. Suppose an individual has to choose between Option A: a 90 per cent chance of receiving 500 Euros and a 10 per cent chance of receiving 0 Euros, or Option B: an 80 per cent probability of getting 400
Euros and a 20 per cent probability of getting 200 Euros. Using the expected utility theory, the person calculates the expected return for both options and then selects the one with the higher value. In this situation, Option A, with an expected return of 450 Euros, would be picked over Option B, which has an expected return of 360 Euros.

While the expected utility theory was the first decision theory under risk and uncertainty, scientists have voiced critique about various assumptions. One point of critique is, the theory assumes that individuals are close to risk-neutral and doesn’t account for risk aversion or risk seeking (Tversky 1975). Another drawback is the theory assumes rationality in decision-making but Kahneman and Tversky (1979) discovered individuals overweight outcomes which are certain. In an experiment, they discovered that people chose a certain option with a lower expected utility over the option with a higher expected utility with a very small amount of uncertainty (Kahneman and Tversky 1979). In general, as many scientists worked on further developing the expected utility theory, many found cases where individuals violated its decision framework and new decision theories emerged (Johnson and Busemeyer 2010).

Although the expected utility theory was the pioneering decision theory addressing risk and uncertainty, various aspects of it have been challenged by scholars. One critique is that the theory presumes individuals to be nearly risk-neutral and doesn't consider tendencies towards risk aversion or risk seeking (Tversky 1975). The theory also assumes rational decision-making, yet Kahneman and Tversky (1979) found that individuals’ tend to assign more weight to certain outcomes. In their experiment, people favoured the certain option with a lower expected utility over the option with a higher expected utility that had a minuscule degree of uncertainty (Kahneman and Tversky 1979). In general, as numerous scientists further developed the expected utility theory, they found numerous instances where individuals' choices deviated from its decision-making framework, leading to the emergence of new decision theories (Johnson and Busemeyer 2010).

In my opinion, while the expected utility theory attempts to anticipate the conduct of rational individuals, the criticisms that humans often act irrationally are well-founded. This suggests a need for a different theory that better mirrors the true behaviour of humans.

2.2.2.2. Prospect Theory
After examining individual decision behaviour within the framework of the expected utility theory, Kahneman and Tversky (1979) found instances where people didn't adhere to its assumptions. As a result, they proposed a new decision theory known as the prospect theory.
Unlike the expected utility theory which assumes individuals make decisions based on outcomes, prospect theory assumes that individuals make decisions based on potential gains and losses relative to a reference point. The central proposition of prospect theory lies in the perception of risk by individuals. It suggests that people are generally risk-averse when they stand to gain something from both decision options - a phenomenon known as the certainty effect (Kahneman and Tversky 1979). Conversely, they tend to be risk-seeking when both decision options could result in losses. In contrast to the expected utility theory, which focuses on the decision-making behaviour of perfectly rational individuals, prospect theory emphasizes how people make decisions.

Figure 3: Value functions of gains and losses in prospect theory (Kahneman and Tversky 1979)

Figure 3 above illustrates how people perceive value when faced with potential gains and losses. As previously mentioned, Kahneman and Tversky (1979) argue that the value function assigned to gains is concave, indicating that people tend to be risk-averse. Conversely, for losses, the value function is convex, suggesting that people tend to be risk-seeking.

To further illustrate the premise of prospect theory, consider the following example. Imagine individuals have to choose between Option A, which offers a 98 per cent chance of gaining 2500 Euros and a 2 per cent chance of gaining nothing, and Option B, which guarantees a gain of 2400 Euros. In this scenario, most individuals tend to choose the safer Option B, despite its lower expected return. On the other hand, let's say individuals are presented with the choice between Option C, which entails a certain loss of 100 Euros, and Option D, which carries an 80 per cent chance of losing 200 Euros. Surprisingly, the majority of people tend to choose the riskier Option D, even though it has a lower expected return. This behaviour can be attributed to the small chance of avoiding any loss associated with Option D. In summary, the example demonstrates that people exhibit risk-averse tendencies when it comes to potential gains, as
they favour safer options. Conversely, when faced with potential losses, individuals tend to display risk-seeking behaviour by opting for options that offer even a small chance of avoiding any loss.

A key characteristic of prospect theory is its focus on short-term outcomes, specifically gains and losses (Kahneman 2003). The theory considers two distinct stages in the decision-making process: the editing phase and the evaluation phase (Kahneman and Tversky 1979). In the editing phase, the decision problem is prepared and inferior options are eliminated. Subsequently, in the evaluation phase, the option with the highest value is selected, taking into account gains and losses (Johnson and Busemeyer 2010). Furthermore, the value function in prospect theory is context-dependent and is determined based on the current reference point and the magnitude of change, whether positive or negative, from that reference point (Kahneman and Tversky 1979). Lastly, prospect theory introduces decision weights, which multiply the value of each outcome, as opposed to the subjective probabilities utilized in expected utility theory (Johnson and Busemeyer 2010).

Although prospect theory holds a prominent position in decision theory, some scholars have raised concerns and identified limitations in its application. Levy (1997) argues that while prospect theory may be suitable for individual choice behaviour, it may apply to more complex issues and high-stakes international relations. Furthermore, the theory has been primarily validated in highly controlled laboratory settings, raising doubts about its generalizability to real-world problems (Levy 1997). Starmer (2000) echoes Levy's (1997) concerns about generalizability and adds that prospect theory fails to account for individual variations in risk preferences. Each individual may have unique risk preferences that are not adequately addressed by prospect theory. Overall, these criticisms highlight the need for caution in applying prospect theory beyond specific contexts and emphasize the importance of considering individual differences in risk preferences when analysing decision-making behaviours.

2.2.3. Bias in Decision-making

In the previous subchapter, we explored prospect theory and highlighted that individuals do not always make rational decisions. Building upon this understanding, the current subchapter will delve into the concept of bias in decision-making. It will examine various biases that exist and specifically focus on their impact on investment decisions. Given that this master's thesis centres around the influence of emotions on investment decisions, this subchapter will
emphasize biases in investment decisions, supported by research in behavioural finance. The objective is to develop an understanding of the biases that can potentially influence an investment decision. Readers will gain insights into what to be mindful of when faced with an impending investment decision.

A bias in decision-making refers to an influence on one's decision that arises from preconceived notions, personal beliefs, past experiences, or cultural backgrounds (Chira et al. 2008). It is common for individuals to possess biases to some extent. According to Dror (2020), biases can be specific to certain cases, influenced by the environment, culture, personal experiences, or even inherent in human nature itself. Interestingly, humans tend to be good at recognizing biases in the behaviour of others, yet they often struggle to identify biases in their actions. Even when individuals are aware of their biases, they may hold an illusion of control over them, falsely believing they have more control than they do (Dror 2020).

The presence of biases in investment decisions was initially uncovered by Kahneman and Tversky (1979) when they introduced prospect theory, which highlighted people's inclination to avoid losses more than seeking comparable gains. This discovery led to the emergence of a new field within finance known as behavioural finance. Unlike traditional finance, which assumes rational behaviour, behavioural finance focuses on studying the actual human behaviour exhibited during investment decisions (Kumar and Goyal 2015). In the subsequent paragraphs, I will delve into common biases observed in investors' decision-making processes.

First, let's delve into the overconfidence bias and how it influences investment decisions. Overconfidence refers to the tendency of individual investors to overestimate their abilities, have excessive confidence in their knowledge, and make investment decisions without thoroughly researching the topic or seeking expert guidance (Chira et al. 2008). This misleading perception of being highly knowledgeable often leads investors to overlook the risks associated with their investments (Kumar and Goyal 2015). Grinblatt and Keloharju (2009) argue that overconfident investors tend to engage in higher trading activity compared to others, although the outcomes are mixed. While it is not possible to generalize whether overconfident traders, on average, achieve greater or lesser financial success, there is evidence that if risk-averse traders exhibit overconfidence in information signals, their overconfidence allows them to effectively exploit that information to a greater extent than rational traders (Hirshleifer and Subrahmanyam 1998).
Another bias that significantly influences investment decisions is the herding bias. Herding bias occurs when individuals deviate from rational decision-making and are swayed by the actions and decisions of others (Kumar and Goyal 2015). This behaviour is often attributed to investors attempting to cope with limitations in information by mimicking the behaviour of their peers (Fernández et al. 2011). Herding behaviour leads to more unpredictable earnings, and reduced trading frequency, and tends to occur more frequently in extreme market conditions (Kumar and Goyal 2015). Based on these observations, I believe the herding bias is likely to have an impact on the behaviour of individual investors in crowdfunding. Further elaboration on this topic will be presented in the next chapter, which specifically focuses on crowdfunding. The current chapter aims to explain various aspects of the broader topic of bias in decision-making.

Furthermore, research has demonstrated the significant impact of confirmation bias on individuals’ investment decisions. Confirmation bias refers to the tendency of individuals to interpret information in a subjective manner that confirms their pre-existing beliefs, often leading them to disregard contradictory or competing information (Chira et al. 2008). This bias can manifest in two ways: information acquisition, where individuals selectively search for information that supports their prior beliefs, and information assimilation, where emerging information is subjectively interpreted as positive (Costa et al. 2017). Confirmation bias influences individuals to view others, companies, or products more favourably if they closely resemble their self-image or if they can identify with them (Chira et al. 2008). In essence, individuals tend to seek out information and interpret it in a way that confirms their preconceived notions, potentially overlooking alternative perspectives or contradictory evidence.

In addition, loss aversion is another cognitive bias, originally identified by Kahneman and Tversky (1979), which significantly affects investment decision-making. Loss aversion theory posits that losses have a stronger emotional impact than gains of equivalent magnitude, and this bias is particularly pronounced when investment decisions are framed in a negative context (Thaler et al. 1997). In other words, losing €100 is perceived as twice as emotionally impactful as gaining €100. This implies that the way an investment decision is framed can play a significant role in whether individuals choose to invest or not, depending on the valence or emotional context of the decision. The awareness of loss aversion and its impact can help us better understand how individuals’ emotions and psychological responses influence their investment choices.
2.2.4. Decision-making in Crowdfunding

The concept of crowdfunding draws inspiration from pre-existing concepts such as micro-finance and crowdsourcing, while also possessing unique characteristics (Mollick 2014). Before the emergence of crowdfunding, the most common ways to raise funds for new businesses involved research grants, support from friends and family, or grants from the government and other institutions (Rossi 2014). However, with the advent of crowdfunding, emerging businesses gained an additional opportunity to secure the required capital by attracting numerous individuals who each invest a small amount in the company.

Crowdfunding initially gained traction within the arts and creative industries in 2006 with the launch of the first crowdfunding platform called Sellaband. One distinguishing aspect of crowdfunding, as exemplified by Sellaband, was its ability to transcend geographical boundaries, allowing people from all around the world to invest (Agrawal et al. 2014). Since then, numerous other crowdfunding platforms have emerged, with Kickstarter being the market leader. The typical process of crowdfunding a business involves submitting a business application to the crowdfunding platform. If the submission is successful, a funding window is usually opened for a specific timeframe within which the funding goal must be reached (Rossi 2014). If the funding goal is achieved, the company receives the invested funds from the crowdfunding platform, and all individuals who invested become investors in the company. However, if the funding goal is not met, all individuals who invested receive their money back, and the company does not receive any funds.

Two of the most common incentives for investors in crowdfunding are reward and equity-based incentives (Vulkan et al. 2016). In reward-based crowdfunding, investors typically receive a product or service in return for their investment. This type of crowdfunding is commonly utilized to pre-finance the production of goods, with investors receiving the final product as a return on their investment (Rossi 2014). Therefore, investors in reward-based crowdfunding are motivated by their interest in the product itself, rather than considering it as a store of value. On the other hand, equity-based crowdfunding offers investors the opportunity to acquire an equity stake in the company. This form of crowdfunding serves as an alternative method for companies to raise funds and is associated with higher risk compared to reward-based crowdfunding (Rossi 2014). In equity-based crowdfunding, investors' primary concern lies in the potential for the company to generate equity value and build a profitable business (Agrawal et al. 2014). Nonetheless, equity-based crowdfunding provides individual retail investors with
unique early access to investment opportunities that are typically not accessible through traditional investment channels (Agrawal et al. 2014).

One notable characteristic of crowdfunding is its low entry barriers for investors, in contrast to the highly regulated traditional financial markets (Hoegen et al. 2018). Crowdfunding offers a convenient alternative for individuals to invest their capital, albeit not without additional risks. Similar to other investment options, investors base their investment decisions on the information provided about the opportunity. However, one challenge with crowdfunding is the difficulty in verifying certain pieces of information (Hoegen et al. 2018). Crowdfunding investments, like many traditional investments, are typically decisions made under uncertainty, as the outcomes are unknown. This uncertainty often leads individuals to rely on the decisions of other investors, resulting in herding behaviour (Vulkan et al. 2016). In the context of crowdfunding, herding behaviour may arise due to the availability of information on the current funding status of a project, which can influence the investment decisions of individuals.

Nevertheless, several other factors play a role in the decision-making process within crowdfunding. Financials and campaign statistics, project and product quality, founder perception and attributes, social communities and third parties, context, and investor characteristics all have an impact on investment decisions in crowdfunding (Hoegen et al. 2018). Financials and campaign statistics provide additional information to potential investors, helping to reduce uncertainty arising from information asymmetries (Greiner and Wang 2010). The quality of the project and product influence decision-making by communicating the potential benefits and rewards investors can expect if the project is successful (Ahlers et al. 2015). How potential investors perceive the competence and skills of the founding team also influences investment decisions, as teams perceived as competent and skilled have a greater likelihood of receiving funding (Mollick and Robb 2016). Social communities and third parties play a crucial role, particularly in the early stages of a funding campaign. The presence of many initial backers tends to attract more participants, while a lack of initial backers can hinder the success of the project (Colombo et al. 2015). Context is another important factor, as the way information is visually presented and how it is framed can influence the decision-making process for potential investors (Choy and Schlagwein 2016). Lastly, investor characteristics also come into play, as individuals often prefer to invest in people and teams that are socially proximate to themselves (Galak et al. 2011). All of these factors collectively influence the investment decisions made within the crowdfunding ecosystem.
2.2.5. Impact of Financial Literacy on Investment Decisions

In the field of financial literacy, there is no single consensus definition. Different scholars and researchers have provided varying definitions of financial literacy. Hung et al. (2009) highlight that financial literacy has been defined inconsistently, encompassing aspects such as specific knowledge, the ability to apply that knowledge, good financial behaviour, perceived knowledge, or general financial knowledge. Huston (2010) argues that financial literacy goes beyond mere knowledge and includes the application of that knowledge in making financial decisions. On the other hand, Fernandes et al. (2014) differentiate between the conceptual and operational definitions of financial literacy. The conceptual definition views financial literacy as a skill and experience necessary to successfully perform product-related tasks, while the operational definition refers to knowledge of financial facts and characteristics. The existence of diverse definitions of financial literacy highlights the potential for variations in the outcomes of studies measuring financial literacy. Consequently, Ouachani et al. (2020) stress the importance of carefully identifying and clearly defining the specific definition of financial literacy to be utilized in a particular study. This approach ensures consistency and comparability among research findings, enabling researchers to draw more meaningful conclusions.

The research community generally agrees on using questionnaires to measure financial literacy. However, there is disagreement among researchers regarding the specific questions and content areas that should be included in these questionnaires (Ouachani et al. 2020). Many studies assessing financial literacy incorporate distinct content areas such as money basics, borrowing, investing, and protecting resources like risk management in their questionnaires (Huston 2010). According to Huston (2010), it is suggested to include three to five questions in each of these four content areas, resulting in a total of twelve to twenty items. In contrast, Lusardi (2019) argues that financial literacy can be assessed with just three questions, known as the "big three." These questions, designed by Lusardi and Mitchell (2011), measure individuals' abilities to perform interest rate calculations, understand inflation, and comprehend risk diversification.

As evident from the discussion, researchers differ in their opinions regarding the number and types of items to include when measuring financial literacy. While these variations can potentially lead to inconsistent results, there is some agreement among studies regarding the content areas to be covered (Ouachani et al. 2020).
After providing an explanation of what financial literacy entails and how it is measured, the subsequent paragraphs will shift the focus towards examining the impact of financial literacy on decision-making and investment behaviour.

Past studies have indicated that financial literacy has a notable influence on decision-making and investment behaviour. According to a study by Kumar (2020), there is a positive correlation between financial literacy and individuals' propensity to invest in the stock market. Furthermore, individuals who score higher on financial literacy quizzes demonstrate greater confidence in making rational and well-calculated investment decisions (Kumar 2020). Additionally, individuals with higher levels of measured financial literacy are more likely to have their retirement planning in order (Lusardi and Mitchell 2017). This suggests that individuals with higher financial literacy are more likely to have a more secure financial future compared to those with lower financial literacy. Moreover, financial literacy enhances individuals' ability to comprehend investment opportunities and acts as a buffer against the negative effects of financial framing (Nieddu and Pandolfi 2020). In conclusion, financial literacy is associated with positive attributes such as rationality and long-term planning. It serves as a valuable tool for individuals to better manage their financial situation and ultimately improve their overall quality of life.

As discussed in the previous paragraphs, financial literacy is believed to have a significant impact on various financial decisions made by individuals. However, establishing a causal relationship between financial literacy and financial decision-making patterns is challenging due to the influence of multiple individual characteristics on financial behaviour (Nieddu and Pandolfi 2020). Nevertheless, research suggests that financial literacy plays a moderating role in mitigating the negative effects of overconfidence bias and contributes to improved investment quality and performance (Ahmad and Ali 2020). Moreover, individuals with higher financial literacy are more likely to effectively manage their budgets and avoid falling into debt (Shahrabani 2012). Consequently, financial literacy is likely to lead to improved financial well-being by facilitating portfolio diversification, increased stock participation, post-retirement preparedness, and wealth accumulation (Sibel and Aren 2017).

2.3. Emotions and Decision-Making
The first two chapters of the theoretical section independently discussed the subjects of emotions and decision-making. Now, my objective is to interweave these topics and delineate the effects of emotions on decision-making and their reciprocal influence. In doing so, I aim to
establish a comprehensible connection between the two subjects and present the current state of research concerning the influence of emotions on decision-making. This concluding chapter of the theoretical section will be partitioned into two subchapters. The first subchapter will concentrate on contemporary literature regarding the influence of emotions on decision-making. Here, I intend to explain how a connection between emotions and decision-making was formed and assess the current level of knowledge. The second subchapter will focus on more specific elements of emotions that influence the decision-making process. In this part, I will scrutinize the impact of individual, distinct emotions, as well as emotional valence and arousal, on decision-making.

Throughout much of the twentieth century, the link between emotions and decision-making was often overlooked. It was widely assumed that individuals made rational decisions, bounded by cognitive and situational constraints (Lerner et al. 2015). However, contemporary perspectives now argue that emotions significantly steer the decision-making process and influence human behaviour. Greene and Haidt (2002) were among the first to propose that moral judgement is not solely a rational activity, but is significantly swayed by emotional intuition. As such, the emotions that arise during the decision-making process can notably influence an individual's choices. The role of emotions in economic decisions was recognized by Lerner et al. (2004) who found that incidental emotions can substantially impact financial decisions. Moreover, they discovered that emotions of the same valence could elicit contrasting investment decisions (Lerner et al. 2004). For instance, fear and anger share the same valence but provoke different reactions and emotions (Lerner and Keltner 2000). Therefore, a more comprehensive framework that considers factors beyond valence is essential for analysing the influence of emotions on decision-making.

The appraisal-tendency framework, introduced by Lerner and Keltner (2000), was designed to tackle the issue of emotions with the same valence but differing impacts on decision-making. A notable characteristic of this framework is its ability to predict how discrete emotions of the same valence can lead to contrasting influences on decisions, and how emotions of opposing valence can prompt similar influences (Lerner et al. 2015). Furthermore, the appraisal-tendency framework differentiates between integral and incidental emotions. Integral emotions involve past subjective experiences, whereas incidental emotions encompass currently perceived experiences. Yet, both types significantly impact consumer decision-making (Han et al. 2007). An intriguing finding by Lerner and Keltner (2001) revealed that the risk perception estimates of angry individuals were closer to those of happy individuals than those of fearful individuals.
In my view, these results provide insightful evidence that contradictory emotions, such as anger and happiness, can put individuals in similar emotional states. Consequently, these individuals may be predisposed to make similar, and potentially biased, decisions.

To mitigate the impact of emotions on an individual's decision-making, Lerner et al. (2015) suggest strategies such as time delay and reappraisal, among others, to facilitate more rational decisions. For instance, an individual experiencing a surge of guilt might be inclined to donate more generously to charity until their emotional state reverts to its previous level over time (Gneezy et al. 2014). Therefore, allowing time to pass is a tactic that can promote more rational decision-making. Reappraisal, another method often successful in regulating emotions, involves reframing the significance of a stimulus into a different perspective. As it occurs early in the emotion-generating process, reappraisal can effectively manage strong emerging emotions that could potentially steer the decision-making process in an undesired direction (Gross 2002).

In conclusion, emotions can influence decision-making in numerous ways, depending on their nature, the specific mechanisms they activate, and the coping strategies employed by individuals (Lerner et al. 2015). However, research focusing on the impact of emotions on decision-making only surfaced towards the end of the twentieth century. In my view, new empirical findings will emerge in the coming decades, potentially altering our current understanding. Therefore, a more comprehensive explanation of how emotions influence decision-making could be on the horizon.

2.3.1. The Cognitive Process of Emotions in Decision-making

The qualitative aspect of emotions stems from neurochemical systems that have been shaped by evolution over time (Buck 1999). These emotional systems are hierarchically organized and are embedded within neurochemical frameworks in the brain. Specifically, emotional systems are situated within the reptilian and limbic regions of the brain (Buck 1999). Buck (1999) proposes that in the human brain, selfish functions are found in the right hemisphere while cooperative functions reside in the left hemisphere. Emotions can also influence judgement and decision-making through several cognitive processes (Petty and Briñol 2015). Furthermore, they suggest that different degrees of elaboration exist in the way emotions impact judgement. Therefore, depending on the level of cognitive processing, emotions are capable of steering judgement in multiple, varied ways. Uniquely, humans possess the ability to regulate emotions through cognitive control. Through interplays between the prefrontal and cingulate control...
systems, as well as the cortical and subcortical emotion-generative systems, humans can selectively engage and alter the significance of a stimulus (Ochsner and Gross 2005).

Attentional control, which determines the amount of attention a stimulus receives, allows individuals to modulate their emotional responses to some degree. If an individual pays limited attention to a stimulus, they can curb the responses in their appraisal systems (Ochsner and Gross 2005). Hence, it appears that humans can minimize distractions by concentrating on the task at hand, reducing the potential for distractions to provoke a response in the appraisal system. Attentional control and emotional regulation have a reciprocal relationship. Attention, cognition, metacognitive processes, and emotions are interlinked, affecting memory, perception, and positive moods, among other processes (Drigas and Karyotaki 2017). Moreover, attentional control might be a valuable technique for regulating emotions in individuals with attention-deficit hyperactivity disorder (ADHD), as these individuals are often more readily distracted by external stimuli (O’Bryan et al. 2017). In my view, it may be challenging for people with ADHD to exercise robust attentional control, given their increased difficulty focusing on a single task. Nevertheless, O’Bryan et al. (2017) suggest that attentional control training during adolescence can enhance individuals' cognition, behaviour, and emotional control.

The cognitive redefinition of emotions is also a promising technique for emotional control. Broadly speaking, cognitive change can be employed to either generate new emotions or regulate an already-initiated emotional response (Ochsner and Gross 2005). Cognitive change can beneficially affect someone's emotional state before, during, and after an event. In all three scenarios, adopting a positive perspective and fostering gratitude are the most effective strategies for regulating and controlling negative emotions (Quoidbach et al. 2015). The brain regions responsible for such cognitive changes and control include the right orbitofrontal cortex and the rostral anterior cingulate cortex (Ochsner 2006). However, the exact operational functions of the regulatory interactions between these brain regions are yet to be fully understood. Breakthroughs are required for us to gain a more comprehensive understanding of these processes (Ochsner 2006).

A person's emotional state significantly influences how they process information and ultimately makes decisions. Individuals in a happy mood tend to engage in top-down processing, relying heavily on pre-existing knowledge instead of gleaning information from the immediate stimuli (Schwarz 2000). On the other hand, those in a sad mood tend to utilize
bottom-up processing, focusing on extracting information from the present stimuli rather than depending on existing knowledge (Schwarz 2000). When compared, bottom-up processing tends to stimulate responses in the amygdala more intensely, while top-down processing triggers stronger responses in the prefrontal regions (Ochsner et al. 2009). Regardless, emotions can be elicited through both aforementioned processes. For instance, fear may be generated in a bottom-up approach by suddenly spotting a spider (McRae et al. 2012). In a top-down approach, emotion might be evoked by reading an unpleasant email (McRae et al. 2012).

2.3.2. Role of emotions during investment decisions

Emotions significantly shape individuals' decision-making processes, including investment decisions. More specifically, an investment decision is influenced by potential and emotional outcomes (Aliya and Bansal 2018). Further, the influence of emotions often gives rise to numerous biases like loss aversion, overconfidence bias, and availability bias, among others, which possibly lead to underperforming investments (Aliya and Bansal 2018). As a result, emotions often negatively affect investment behaviour, with rational investors typically outperforming their emotional counterparts. Shiv et al. (2005) carried out a study comparing the investment behaviour of individuals with brain damage affecting emotional processing to completely healthy individuals. They found that the group with emotional processing impairments outperformed the healthy group. While the healthy participants' decisions were swayed by previous outcomes, the other group made unbiased decisions, yielding better results (Shiv et al. 2005). Considering that past research suggests emotions predominantly harm investment performance, I firmly believe it's essential to delve deeper into the role emotions play in investment decision-making.

For a considerable duration, many researchers held the belief that decisions, including investment decisions, could be forecasted based on individuals' emotional valence. For instance, Zou et al. (2011) posited that the emotional tone of online product reviews impacts less experienced consumers more than their more experienced counterparts. However, Lerner et al. (2015) assert that emotional valence is merely one of the multiple dimensions influencing decision-making. Given that emotions sharing the same valence can evoke diverse behaviours, they propose that an appraisal-tendency framework, encompassing multiple dimensions, is more suitable for predicting decisions. George and Dane (2016) highlight the significant influence of core affect on decision-making. Core affect refers to the fundamental feelings of positivity or negativity, or feeling energized or drowsy (Russell 2009). In the context of investment decisions, Seo and Barrett (2007) concluded that experiencing feelings during the
decision-making process can be advantageous. Individuals who can identify and differentiate their emotions achieved superior outcomes, as they were aware of potential biases that could arise from the feelings they were experiencing (Seo and Barrett 2007). Therefore, affect doesn't necessarily detract from the performance of investment decisions, provided individuals can identify their current emotional state. Besides, if an investor's affect towards something is positive, they perceive the risk as low and the benefits as high (Finucane et al. 2000). It thus seems plausible that investors tend to invest in companies or products they favour, as they perceive the risk as more favourable than it is.

In addition to affect, individual discrete emotions such as anger can influence investment decisions. For example, the manifestation of anger in investors tends to steer them towards riskier investment behaviour (Gambetti and Giusberti 2012). Further, the trait of anger led people to diversify among risky assets, resulting in better performance compared to the trait of anxiety, where investors diversified mainly among less risky assets yielding lower returns (Gambetti and Giusberti 2012). Thus, anger serves as a predictor for riskier investment behaviour, which is not necessarily disadvantageous as risky assets can lead to high returns, particularly during good market conditions. Bernaola et al. (2021) corroborate (Gambetti and Giusberti 2012) assertion; their study found that participants who experienced anger were more likely to invest in the riskiest asset class, indicating a positive correlation between anger and risky investment behaviour. In addition to anger, gender also predicts investment behaviour, with males being significantly less risk-averse than females (Bernaola et al. 2021). Furthermore, angry investors tend to spend less time seeking additional information relevant to an investment decision compared to fearful investors (Wynes 2021). Consequently, anger can foster more intuitive decision-making, placing greater reliance on individuals' basic instincts.

While the specific influence of the discrete emotion of desire on investment decisions hasn't been thoroughly examined, studies investigating desire's role in decision-making and marketing strategies have provided intriguing insights. Desire persistently exists in the human mind, often subconsciously (Pettit and Smith 1990). This background desire is omnipresent when individuals are deliberating between choices, subtly influencing their decisions (Pettit and Smith 1990). The desire for rewards can make us susceptible to poor judgement and entice us with misleading promises (Morse 2006). Marketing tactics commonly aim to arouse consumers' desires, prompting them towards purchases (Rani 2014). Brands create a sense of desire by establishing awareness of a product's necessity for something that consumers
currently lack (Rani 2014). From my perspective, desire exerts an impact on virtually every decision-making process, often operating outside of our conscious recognition. This most likely includes investment decisions, which, as suggested by Aliya and Bansal (2018), are typically not completely rational. As such, it is plausible to infer that desire also plays a role in shaping investment decisions.

Additionally, financial literacy serves as a moderator in the relationship between emotions and investment behaviour. Financially literate investors are less likely to engage in herd behaviour and more likely to base their investment decisions on their personal beliefs (Baker et al. 2018). Moreover, financial literacy helps diminish the detrimental impact of overconfidence bias on investment performance, as well-educated investors are less likely to make impulsive decisions (Takeda et al. 2013). Thus, financially literate investors tend to base their investment decisions on their knowledge and experience, being less influenced by behavioural biases. Furthermore, financial literacy is associated with emotional intelligence. Therefore, possessing financial literacy enables individuals to exercise greater control over their emotions and understand them more effectively (Hadi 2017). In conclusion, I believe that financial literacy is likely to mitigate the influence of emotions on investment decisions for the reasons stated above, facilitating a more rational approach to investing.

Emotions not only influence decision-making in traditional investments such as stocks but also in emerging types of investments like crowdfunding. Unlike financial experts who typically employ frameworks to ensure rational decision-making, individual backers of crowdfunding projects often make investments driven by emotion (Ren et al. 2021). Additionally, these backers are frequently swayed by project descriptions and thereby experience arousal (Ren et al. 2021). Specifically, innovative crowdfunding projects can elicit positive emotions, which tend to motivate individuals to impulsively support such projects more often than projects perceived as less innovative (Yi et al. 2022). This suggests that novel ideas are likely to attract more funding from impulsive backers compared to conservative ideas. Moreover, the success of a crowdfunding project depends on the stimuli presented. For instance, more complex logos are associated with innovativeness and tend to positively guide backers' funding decisions (Mahmood et al. 2019). Beyond emotional influences, backers' decisions in crowdfunding are also affected by behavioural biases. In reward-based crowdfunding, backers usually have the choice between multiple rewards. Due to the middle-option bias, backers tend to invest more than the minimum but less than the maximum (Simons et al. 2017). In conclusion, backers of crowdfunding projects make decisions driven by emotions and are influenced by behavioural
biases. Hence, a more in-depth examination of the discrete emotions and other factors affecting backers' decision-making could be beneficial in gaining a better understanding of their behaviour.

2.3.3. Affective Computing and Emotional Expressivity

Affective computing is an emerging field in computer science that focuses on measuring affect, or emotional states, through facial expressions using machine learning techniques. This field departs from traditional emotion theories posited by philosophers and psychologists, which were previously the foundation for emotion research and used to interpret human behaviour (Calvo and D’Mello 2010). The objective of affective computing is automated emotion measurement, and it draws on two primary emotion theories. The first is the discrete emotion theory proposed by Ekman and Friesen (1971), which posits that particular facial expressions correlate with distinct emotions. The second is Russell’s (1980) circumplex model of affect, which categorizes affect according to dimensions, such as valence and arousal. Hence, affective computing measures both discrete emotions and the valence and arousal levels of individuals through their facial expressions. The accuracy of automated models in reading emotions through facial expressions has significantly improved, reaching a success rate of about 90 to 95 per cent, depending on the database and method employed (Mollahosseini et al. 2019). The advantages of affective computing encompass the capacity to measure facial expressions more extensively than humans can, the ability to provide in-depth analytical insights, the flexibility to develop universal or specific models, and the capability to incorporate these models into real-time closed-loop systems (D’Mello et al. 2018).

The majority of techniques necessary for automated affective computing employ machine learning methodologies and rely heavily on a large volume of training data in the form of facial expressions (Mollahosseini et al. 2019). Although several databases exist that store facial expressions captured in controlled laboratory environments, AffectNet and SEWA are two databases that specifically hold facial expressions captured from real-life scenarios (Mollahosseini et al. 2019; Kossaifi et al. 2021). AffectNet contains a million facial expressions from 450,000 individuals and outperforms traditional machine learning methods (Mollahosseini et al. 2019). Automated affective computing systems have a quantitative edge in analysing facial expressions. However, other factors also come into play, and it may take a while before these systems can surpass humans qualitatively in assessing emotions. Despite this, D’Mello et al. (2018) propose that ongoing advancements in big data, wearable sensing, crowdsourcing, and deep learning will continue to enhance affective computing. They predict
that these improvements will likely enable affective computing to outperform humans in emotion sensing in the future.

Emotional expressivity through facial expressions is a prerequisite for affective computing to measure emotions. A key challenge lies in accurately predicting an individual's internal emotions, especially when they are intentionally concealed behind deceptive facial expressions (Wang et al. 2022). Thus I believe, models are better equipped to accurately decipher the emotions of emotionally expressive individuals. It is comparatively easier to interpret the emotional state of such individuals through their nonverbal cues. Emotional suppression is associated with a decreased heart rate and increased blinking (Gross and Levenson 1993). Furthermore, the suppression of emotions does not affect the subjective experience, meaning that humans experience emotions the same way, whether suppressed or not (Gross and Levenson 1993). In conclusion, an individual's emotional expressiveness can impact the accuracy of automated affective computing systems, particularly when individuals display deceptive or absent facial expressions. To improve the performance of such models, it would be advantageous to train them to detect misleading indicators such as excessive blinking.

2.4. Theoretical Framework

In this section, I will clarify how I developed my hypothesis and specify the hypothesis I chose to test. Since I have already discussed the theoretical background in previous sections, I aim to keep the derivation concise and avoid unnecessary repetition. Generally, a hypothesis is an informed speculation that is formulated to be tested to understand the relationship between two or more variables (Bryman and Bell 2015). Thus, I formulated hypotheses about possible relationships between emotions and investment decisions based on the theoretical background of what is already known in this research area. In Figure 4 below the theoretical framework is visualised.
Before addressing the research question about the influence of financial literacy on emotions and investment decisions, it is crucial to first explore the impact of emotions on investment decisions. Investment decisions are influenced by emotions (Aliya and Bansal 2018; Shiv et al. 2005) and hence impact the performance of those investment decisions. The effect of desire in decision-making has been analysed (Morse 2006; Pettit and Smith 1990) but little is known about the impact of it in the specific case of an investment decision. However, since desire is positively correlated with purchases (Rani 2014), I concluded with the following hypothesis:

**H1a: Expressed desire as a discrete emotion is positively related to investment decisions. The higher the level of measured desire the more likely an investment decision was made.**

On the contrary, parts of the effect of anger on the investment decision have been studied. The emotion of anger leads to riskier investment decisions (Gambetti and Giusberti 2012; Bernaola et al. 2021) and spending less time gathering additional information (Wynes 2021). Still, there is a gap in our understanding regarding the frequency of investment decisions and the specific influence of anger on these decisions. Based on the fact that anger leads to less time gathering additional information, I deduced the following hypothesis:

**H1b: Expressed anger as a discrete emotion is positively related to investment decisions. The higher the level of measured anger, the more likely an investment decision was made.**

Core affect can be favourable in investment decisions if individuals are aware of their attitude towards a stimulus (Seo and Barrett 2007). In addition, positive affect reduces the risk perception of individuals towards a stimulus (Finucane et al. 2000). Thus, I expect a positive
relationship between core affect and investment decisions and established the following hypothesis:

**H1c:** The core affect, as the interaction of expressed valence and arousal, is positively related to investment decisions. The higher the level of measured core affect, the more likely an investment decision was made.

Financial literacy reduces emotional biases (Takeda et al. 2013) and thus leads to more rational decision-making. Further, financial literacy leads to less herding behaviour (Baker et al. 2018) and those individuals have better emotional control (Hadi 2017). The influence of financial literacy on emotions in investment decisions isn’t known so far. However, based on the general impact of financial literacy on investment decisions, I expect it to have a moderating effect on the role of desire, anger and core affect on the investment decisions. Therefore, I concluded with the following hypotheses:

**H2a:** Financial literacy, measured through the point total of the financial literacy quiz, moderates the relationship between desire and investment decisions. The higher the level of financial literacy, the weaker the correlation between desire and investment decisions.

**H2b:** Financial literacy, measured through the point total of the financial literacy quiz, moderates the relationship between anger and investment decisions. The higher the level of financial literacy, the weaker the correlation between anger and investment decisions.

**H2c:** Financial literacy, measured through the point total of the financial literacy quiz, moderates the relationship between core affect and investment decisions. The higher the level of financial literacy, the weaker the correlation between core affect and investment decisions

In crowdfunding, investors let their decision be influenced by multiple factors including the funding status. Funding goal close to being accomplished typically leads to herding behaviour as investors tend to follow the crowd (Vulkan et al. 2016). Therefore, I deduced the following hypothesis:

**H3a:** The additional information that 90% of the funding target has been reached at the halfway point of the funding campaign will lead to an increase in ECUs invested compared to no information about the funding status.
However, if the crowdfunding campaign struggled to recruit investors early into the crowdfunding campaign, the campaign most likely fails to meet its funding goal (Colombo et al. 2015). Hence, I concluded with the following hypothesis:

**H3b: The additional information that 25% of the funding target has been reached at the halfway point of the funding campaign will lead to a decrease in ECU's invested compared to no information about the funding status.**

Marketers try to create desire in their potential customers to convince them to purchase (Pettit and Smith 1990). Hence, desire leads humans to act irrationally and make bad judgments. I expect the funding goal of 25% reached halfway through the crowdfunding campaign to lead to less investment and only irrational individuals will invest. Thus, I expect the emotions of desire to be a positive influence in that investment scenario. Therefore, I concluded with the following hypothesis:

**H3c: The additional information that 25% of the funding target has been reached at the halfway point of the funding campaign moderates the relationship between desire and the investment decision. The positive influence of desire on the investment decision is stronger when the additional information of the funding goal is 25% accomplished is provided, compared to when it's not.**

2.5. Limitations

As I conclude my literature review, it is important to acknowledge the potential limitations inherent in this study. The primary objective of this master thesis is to deepen our understanding of how emotions influence investment decisions. However, it is crucial to recognize that this exploration, while comprehensive, will not render further research in this area redundant. The complexity of emotions and their impact on investment decisions necessitates ongoing investigation. This study is a step forward in this multifaceted field, but it is by no means a conclusive end.

2.5.1. Scope of existing literature

Lerner et al. (2015) highlight that research into the emotional influence on decision-making, including investment decisions, only truly began towards the end of the last century and has been gaining momentum over the past decade. As such, this field is still in its early stages, with numerous areas yet to be explored. For instance, it was previously assumed that valence alone could predict decision-making processes, but recent studies have challenged this notion. Some researchers now propose that affect, the interplay between valence and arousal, is a more
accurate predictor of decisions (Rupp et al. 2023). However, it remains to be seen whether this perspective will be solidified in future research or if new findings will suggest alternative viewpoints. Furthermore, given the existence of competing emotion theories, it is impossible to assert with absolute certainty that the application of both discrete emotion theory and dimensional emotion theory was the optimal approach to measuring individuals' emotions.

In addition to the influence of emotion on investment decisions, the definition, measurement, and applicability of financial literacy are also subjects of ongoing debate. Firstly, there is no universally accepted definition of financial literacy, which complicates comparisons between studies that use different definitions. Secondly, there is disagreement among scholars regarding the optimal method for measuring financial literacy. This includes debates over the number of items a questionnaire should contain and the specific topics of financial literacy that should be covered (Ouachani et al. 2020). I believe it's crucial to acknowledge these challenges when measuring and interpreting financial literacy. Despite these limitations, I maintain that financial literacy could potentially influence the impact of emotions on decision-making. Furthermore, the financial literacy quiz developed by Fernandes et al. (2014) is widely recognized as a valuable tool for assessing financial literacy.

2.5.2. Scope of my literature review

Furthermore, it's important to acknowledge that my literature review may not have encompassed all the elements that could potentially influence the relationship between emotions and investment decisions. The primary objective of this thesis was to scrutinize the interplay between emotions, financial literacy, funding status, and investment decisions. To achieve this, I delved into literature spanning the fields of psychology, finance, and innovation management. Despite my diligent efforts to review all the pertinent literature, it's conceivable that some relevant studies may not have been included. This could be due to a few reasons. One significant factor is time constraints. With limited time, it's challenging to peruse every article on these topics or to continually seek out fresh perspectives. The field is vast, and new research is being published continually. Another factor is the breadth of relevant theories. Theories from other disciplines, not just psychology, finance, and innovation management, might also be relevant to the relationships under investigation. However, to ensure the comprehensibility of this thesis and to avoid becoming mired in every conceivable aspect that could influence these relationships, it was necessary to set boundaries on the scope of this master thesis. Therefore, this thesis concentrates on these relationships. It's a stepping stone, a way to begin understanding this intricate relationship. But it's not the final word. Future
research should continue where this leaves off. Researchers should persist in exploring, delving deeper, and incorporating new findings. This will help us progressively enhance our understanding of this complex relationship.

2.5.3. Measurement of emotions

The last limitation I want to talk about is how we measured emotions. This thesis uses data from affective computing, specifically TAWNY, and the Discrete Emotion Questionnaire (DEQ) developed by Harmon-Jones et al. (2016), which participants filled out themselves. First, applying affective computing with TAWNY to measure emotions might not be completely accurate. TAWNY looks at people's facial expressions, so it depends on how much people show their emotions on their faces. If there's no change in facial expressions, it would be hard for TAWNY to spot any change. Also, according to Mollahosseini et al. (2019), the chance of correctly identifying emotion from facial expressions is about 90 to 95 per cent. So, there's a chance that TAWNY could get a facial expression wrong and link it to the wrong emotion. On top of that, TAWNY might pick up emotion that a participant felt while watching the video, but that emotion might not be because of the video. For example, a participant might remember something funny or distracting, which could affect the emotion that TAWNY detects.

Secondly, participants were asked to self-report their emotions experienced while watching the pitch video using the DEQ. To make sure participants could still remember their feelings during the video, the DEQ was the first questionnaire they filled out after watching it. However, self-reported emotions are often subjective, which can lead to limitations. More specifically, self-reporting can affect the internal validity, external validity, and construct validity of the study, among other factors (Brutus et al. 2013). One issue that can arise is a response bias known as socially desirable responding. This is when participants might not answer truthfully because they want to make themselves look better (Van de Mortel 2008). During the DEQ, this could happen because we ask about their desire and anger, and participants might answer these questions in a way that makes them look more positive. To try to prevent this, we made sure that individuals' responses were anonymous, so no one could link their answers back to them. However, participants might still feel pressure to present themselves in a more positive light due to social norms.
3. Methodology and Research Design

This chapter focuses on the process of how I approached and designed the experiment to answer the following research questions: How did economic knowledge impact the role of emotions in investment decisions for retail investors in crowdfunding? and How did the funding status impact the investment decisions of retail investors? The chapter includes the research design, data collection and sampling strategy, experimental setup, ethical considerations, and limitations. A detailed explanation for all previously mentioned subtopics is provided. Thus, this chapter discloses the process of the setup of the experiment to link the ensuing results with existing theory to eventually answer my research questions.

3.1. Research Design

The research design employed to address the research questions was experimental, specifically falling into the category of laboratory experiments. This design allowed for the analysis of the interaction between emotions and investment decisions. Laboratory experiments offer advantages such as greater control over experimental arrangements compared to field experiments (Bryman and Bell 2015). In this experiment, a laboratory-like setup was created using a video of a closed crowdfunding pitch, and the groups were weighted equally to ensure an approximately equal number of participants in each of the four groups. This level of control would likely not be feasible in a field experiment where participants can self-select their preferred settings, making it difficult to control the stimuli and group sizes effectively. The experiment consisted of two key components. Firstly, structured observations were conducted using affective computing techniques from TAWNY to observe participants' behaviour while watching the pitch video. Secondly, participants completed questionnaires comprising closed-ended responses to make their investment decisions and other choices.

More generally, a deductive research approach was employed in the study. This involved formulating hypotheses based on existing theories and prior knowledge and subsequently testing these hypotheses using empirical data. This research strategy aligns with positivism, an epistemological stance influenced by an objectivist ontological perspective (Bryman and Bell, 2015). The research approach was also aligned with objectivism, ensuring independence from personal biases or interpretations. Additionally, the collected data was analysed quantitatively, employing statistical analysis to measure and analyse variables. This quantitative analysis allows for the generalizability of results to a larger population (Bryman and Bell 2015).
3.2. Sampling Strategy and Data Collection

The sampling strategy for the study was a non-probability convenience sample. A benefit of this sampling strategy was that participants were selected based on availability, making it a cost-effective approach (Acharya et al. 2013). Thus, anyone with time and willingness could participate in the study. Since the research questions did not target the analysis of a specific demographic, the sampling strategy was suitable for addressing the research questions. To increase accessibility and achieve a more diverse sample size, the experiment was conducted online. This approach made it easier for people to participate, as they were not limited by their location and the additional time commitment (Wright 2005). Therefore, experimenting online was necessary to ensure broader participation and meet the deadline. Collecting data in person would not have been feasible within the given time frame.

Furthermore, to achieve the research objectives, primary data was collected. The primary data was gathered through an experiment, allowing for a causal interpretation of the outcomes (Hox and Boeije 2005). Throughout the experiment, data were collected using multiple questionnaires, as well as the AI-based emotion analytics platform TAWNY, which employs AI algorithms to analyse human affective states (TAWNY 2022). TAWNY utilizes the front camera to measure various emotional states, including valence, arousal, happiness, surprise, anger, and sadness. It also records individual heart rate and attendance data. TAWNY collected data points every second for each of the aforementioned variables. Additionally, the experiment was conveniently distributed by providing access links through email, private messaging, social media, and other distribution channels. This form of participant recruitment proved to be more time-effective compared to offline recruitment methods (van Selm and Jankowski 2006). Moreover, online experiments offer several advantages, including easier administration through real-time participant counts tracking and simplified data preparation for analysis.

3.3. Experimental Setup

In the following paragraphs, I aim to provide a detailed explanation of the experiment's structure and the relevance of each component. It is important to note that the experiment was designed in collaboration with a fellow student who analysed a similar topic. Therefore, the subsequent paragraphs were written in the "we" form to reflect our joint effort and shared expertise.

We set up the experiment on two different platforms, the first part on tawny.ai and the second part on limesurvey.com. The initial four questions on each website were designed to create a
private key, linking the collected data across both platforms. We crafted the questions in such a way that each participant had a unique private key composed of the first letter of their mother's and father's first names, the day they were born, and the last letter of their first name. Subsequently, we collected general information about each participant, such as age, gender, education level, and current employment status. We required this information to understand the basic characteristics of our sample group. Thereafter, we asked participants about their mood on the day they partook in the experiment, questioning whether they felt bad or good, unpleasant or pleasant, sad or happy. Roehm and Roehm (2005) presented these three questions in the form of a Likert scale, ranging from 1 to 5. On this scale, 1 represented a highly negative response, while 5 signified a strongly positive response. Given that mood has been identified as a factor influencing individuals' investment behaviours (Aliya and Bansal 2018), collecting information on participants' moods seemed logical.

Participants were then shown a two-minute pitch video from a company seeking to raise capital. During the video, TAWNY recorded the participants through the front camera, capturing their emotional responses and collecting data points every second. To ensure that the video would elicit emotional responses, we conducted a preliminary study with nine participants. We recorded these individuals watching five different pitch videos and measured their emotional responses. After analysing the collected data from TAWNY, we chose the video that evoked the widest range of emotional responses by examining which video had the largest standard deviation in emotional responses. Ultimately, we selected a pitch video from THIS™, a company producing plant-based meat alternatives. As plant-based meat alternatives often provoke diverse reactions, this held for our participants as well. This video had the largest standard deviation in most of the emotional variable values and was thus suitable for our experiment.

Following the video, we redirected participants from www.tawny.ai to www.limesurvey.com, where they were first asked the four identification questions to recreate their unique private key. Afterwards, participants were randomly assigned into one of four groups, each of which was designed to have roughly the same number of participants. The groups differed by crowdfunding type - either equity or reward-based - and by the funding status of the project, which was either 25% or 90% of the funding goal reached halfway through the crowdfunding campaign. Thus, the four groups were Equity 25%, Equity 90%, Reward 25%, and Reward 90%. Once the group allocation was completed, respondents were asked to self-report their emotions experienced while watching the video. We used the Discrete Emotion Questionnaire
(DEQ) developed by Harmon-Jones et al. (2016) to gather these self-reported emotions. The DEQ uses a Likert scale, ranging from 1 to 7, to assess discrete emotions experienced by individuals. We analysed the discrete emotions of anger and desire and asked participants how much they experienced wanting, desire, longing, anger, rage, being mad, and being pissed off. Since all seven emotion items belong to the emotional families of desire or anger, we took the average score of each emotional family into consideration.

Subsequently, participants were asked to make an investment decision. At this point, they were not informed about the funding status but were aware of the crowdfunding type. There were two different scenarios: either equity or reward-based crowdfunding. However, these distinctions were not relevant to my thesis as were not considered in the analysis of this thesis. Each respondent was given a budget of 1,000 experimental currency units (ECUs) and had the option of making no investment or investing in increments of 250 ECUs, up to a maximum of 1,000 ECUs. ECUs, a commonly used currency in financial experiments as referenced by Hanaki (2022), were later converted into real currency for participant pay-outs. One advantage of using ECUs was that it created the perception among participants that they were investing a larger sum of money than they were. This perception resulted in a heightened sense of importance and seriousness towards the experiment as if they were investing a substantially smaller amount in Euros.

After the initial decision, we presented participants with another investment opportunity, this time incorporating information about the funding status of the crowdfunding project. Again, four scenarios were available, but only two were pertinent to my thesis since I did not differentiate between equity and reward-based crowdfunding. We chose two different funding statuses to examine the herding behaviour of individuals - specifically, whether small funding amounts led to less investment (Zaggl and Block 2019), and whether large funding amounts induced herding behaviour among individuals (Astebro et al. 2018). Once again, participants had the choice of not investing or investing in increments of 250 ECUs, up to a maximum of 1,000 ECUs. To provide a more realistic scenario, we showed participants a mock-up dashboard displaying the funding status before they made their investment decisions.

Following the two investment decisions, we asked respondents questions regarding their emotional expressivity and their evaluation of the product idea from THIS™. We assessed emotional expressivity through four questions developed by Kring et al. (1994) which focused on participants' emotional expressiveness. The responses were gauged using a Likert scale
ranging from one to seven, where one stood for "strongly disagree" and seven for "strongly agree". We included these questions to better understand the data TAWNY collected from participants as they watched the pitch video. Participants who exhibited minimal facial expressions were likely to report lower emotional expressivity, while those with more expressive faces were expected to report higher emotional expressivity. To assess participants' perception of the product's idea and potential, we asked them to answer five questions, which were adopted from Blohm et al. (2016). The responses were again gauged using a Likert scale, this time ranging from one to five, with one indicating "very low" and five "very high".

The final set of questions in our experiment, pertinent to my research question, focused on financial literacy. We adopted the financial literacy questionnaire from the work of Fernandes et al. (2014), which Hanaki (2022) further refined with minor modifications. This questionnaire consisted of twelve multiple-choice questions that covered basic financial principles such as saving, investing, managing debt, and understanding interest rates. The questions varied in difficulty and included options for "Don't know" and "Refuse to answer", ensuring respondents weren't compelled to answer if they were unsure. We awarded one point for each correct answer, with no deductions for wrong answers, and the final score was the total of all points earned during the quiz. In Hanaki's (2022) study, the average score among students on the financial literacy quiz was 8.5. Given that our sample wasn't specifically aimed at students or individuals with financial knowledge, we anticipated a lower average score. With twelve questions, our questionnaire fell within the range suggested by Huston (2010), which made us confident that it was suitable for measuring our participants' financial literacy.

To conclude the observation phase, we presented participants with several control questions to better understand who had participated in the experiment. These queries focused on prior financial experiences, risk behaviour, and dietary habits. We asked participants whether they had invested in any financial products in the past, assuming that those with such experiences would likely have a better understanding of financial principles. To gauge risk behaviour, we used two questions from Razen et al. (2020) that measured respondents' general willingness to take risks and their willingness to do so when making investment decisions. Responses were gauged on a Likert scale, ranging from one to ten, with one signifying "Not at all willing to take risks" and ten "Very willing to take risks". According to Razen et al. (2020), there is a correlation between the responses to these questions, suggesting that individuals inclined to take risks generally are also likely to do so when making investment decisions. Finally, we asked participants about their dietary habits, specifically their preference for meat alternatives.
This was relevant to our study as their investment decisions were based on a company producing such alternatives. We theorized that those who disliked these alternatives or followed a meat-heavy diet might be less inclined to invest in the product.

3.4. Main Variables and Data Analysis

The following paragraphs aimed to discuss the variables relevant to my analysis. The dependent variable for my analysis was the investment decision in crowdfunding, with all analyses being based on this. I labelled responses to this question as 1 for "Yes" and 0 for "No", creating a dummy variable. The independent variables that I anticipated to predict investment decisions were the discrete emotions of desire and anger, the core affect, and the funding status. I assessed the discrete emotions of anger and desire using the Discrete Emotion Questionnaire (DEQ), with each emotion calculated based on the average of all items within their respective emotion family. Core affect denoted the interaction between expressed valence and arousal, both of which TAWNY measured through facial recognition. The independent variable of funding status considered whether participants invested more if 90% of the funding goal had already been achieved and less if only 25% of the funding goal had been reached. Consequently, I created two separate independent variables: funding_status_90 and funding_status_25.

Furthermore, in my analysis, I included a moderator to test if they influenced the relationship between the discrete emotions of anger and desire, as well as core affect and investment decisions. The moderator I incorporated was financial literacy. I gathered data for the moderator through financial literacy. The variable of financial literacy was the sum of all correct answers throughout the financial literacy quiz. Each correct answer was worth one point, with no deductions, so the highest possible score was twelve and the lowest was zero. In addition to the main variables, I incorporated several control variables to address potential confounding factors. These control variables were the participants' level of risk aversion and idea evaluation. I included these control variables in my analysis because both factors could potentially impact the investment amounts. My aim in including these control variables was to gain a more comprehensive understanding of the actual relationships among all variables, rather than solely considering the main variables.

To investigate the influence of emotions on investment decisions and the moderating effect of financial literacy, I performed logistic regressions. Each logistic regression model incorporated the dependent variable, which is the investment decision, alongside an independent variable.
such as desire, and control variables like risk aversion and eating habits. Depending on the specific hypothesis under examination, a moderator such as financial literacy was either included or excluded. The purpose of using logistic regression was to estimate how independent variables and moderators affect changes in investment behaviour. For the comparison of two means, necessary for testing hypotheses H3a and H3b, I utilized the Wilcoxon signed-rank test, which is suitable for data that is not normally distributed (Field et al. 2012). To test the moderating effect of the funding goal being 25 per cent achieved halfway through the crowdfunding campaign on desire, I employed a linear mixed-effects model. In this instance, the data for the investment decision, desire, and funding status were duplicated and linked by the token id, allowing for a comparison of the influence of desire on the investment decision before and after the revelation of the funding status.

3.5. Ethical Considerations
From the outset of planning our experiment, we were meticulous about adhering to ethical guidelines and best practices. Crucial considerations for such work include safeguarding participants, clearly communicating the terms of participation, maintaining participant confidentiality, ensuring informed consent, and securely managing data, as discussed by Bryman and Bell (2015), and Saunders et al. (2009). Even though our online experiment didn't pose a physical risk to participants, we were mindful of potential emotional impacts. For instance, TAWNY was used to record participants' facial expressions during the experiment, raising privacy concerns that we were keen to address.

The importance of ensuring the privacy of these recordings was paramount. Any leaks could cause significant embarrassment and emotional distress for the individuals involved. Therefore, once the necessary data were extracted from these videos, we promptly deleted all recordings. Furthermore, we made certain that all participants were fully aware that we would be recording their facial expressions during the experiment. We assured them of their right to withdraw from the experiment at any time, in our bid to make everyone feel comfortable and maintain a sense of control.

3.6. Limitations
Utilizing a non-probability convenience sample was a cost-effective approach that simplified the process of gathering participants for our experiment. However, this method does come with certain limitations, such as the difficulty in generalizing results to a broader population and the potential introduction of selection bias, as highlighted by Acharya et al. (2013). Due to the
nature of convenience sampling, it wasn't possible to assert that our findings could be applied to the broader population. Still, despite this limitation, we could draw valid conclusions about the specific group under our study.

Selection bias refers to the potential distortion of results due to the selection of participants. In convenience sampling, researchers often opt for the most accessible or easiest-to-reach individuals. This could lead to a scenario where the chosen participants share certain characteristics, hence not being representative of the entire population, as described by Hernán et al. (2004). For instance, our study primarily recruited participants through channels like personal networks, social media, and university email lists, resulting in a sample predominantly comprising students. Therefore, our sample was not perfectly representative of the broader population. Nevertheless, despite this limitation, we believe our study provides valuable insights. We specifically shed light on the interplay between investment behaviours among individuals and the role of emotions in these decisions. Although our findings may not be generalizable to all, they offer interesting data about the specific group under our study.
4. Results and Findings

This section is dedicated to describing the systematic process undertaken for analysing the data. Conveniently, it's divided into two parts: an examination of descriptive statistics and a more in-depth exploration of statistical analysis. In the first part, the focus is on descriptive statistics. In this section, I delve into the attributes of the sample and other significant factors gathered during our study. For example, I evaluate the results of the financial literacy quiz, assess the level of emotional expressivity demonstrated by our participants, and explore the emotions they experienced while watching our video, as well as those emotions they recognized within themselves. Moving forward, the second part zeroes in on statistical analysis where I thoroughly investigate my hypotheses, providing answers to the research questions I've posed. Additionally, an assessment for reliability and validity is conducted, ensuring the strength and credibility of the collected data.

4.1. Descriptive Statistics

4.1.1. Demographics of the Sample

The sample consists of a total of 121 participants excluding those with incomplete values. Tables 1 and 2 present the data gathered from the participants. The participants ranged in age from 17 to 66, with an average age of 27.4 years. The sample primarily comprised females, with 72 in total, along with 48 males and one individual identifying as diverse. Additionally, the majority of participants were highly educated, mirroring the demographic from which we recruited for our experiment. A total of 59 participants held a bachelor's degree, 37 had completed their Abitur or Matura, 15 held a master's degree, nine had other forms of education, and one held a doctoral degree. Furthermore, the sample was largely made up of students, 89 in total, with the majority of the remaining participants being employed (29 individuals), and one person being retired.

<table>
<thead>
<tr>
<th>Table 1: Descriptive statistics - age summary</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
</tr>
<tr>
<td>17</td>
</tr>
</tbody>
</table>
4.1.2. Control Variables

During the experiment, we collected data on control variables such as eating habits, mood, and risk aversion. Table 3 displays the eating patterns of the participants. Almost 70 per cent of participants favour meat substitutes, which is significant given that the investment decisions revolve around a company that produces these substitutes. Furthermore, only 23 per cent of participants follow a meat-intensive diet. The majority of participants, approximately 72 per cent, primarily consume vegetarian meals, while about 13 per cent mainly opt for vegan food. It's crucial to mention that the response options about diet were not mutually exclusive, allowing a participant to indicate both vegetarian and vegan preferences. Therefore, a total of 100 per cent is only achieved in each binary (yes or no) question, and not across all questions related to eating habits.
### Table 3: Descriptive statistics - eating habits of the participants

<table>
<thead>
<tr>
<th>Variable</th>
<th>Values</th>
<th>Frequency</th>
<th>Per centage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eating substitutes</td>
<td>Yes</td>
<td>83</td>
<td>68.60%</td>
</tr>
<tr>
<td></td>
<td>No</td>
<td>38</td>
<td>31.40%</td>
</tr>
<tr>
<td>Eating meat heavy</td>
<td>Yes</td>
<td>28</td>
<td>23.14%</td>
</tr>
<tr>
<td></td>
<td>No</td>
<td>93</td>
<td>76.86%</td>
</tr>
<tr>
<td>Eating vegetarian</td>
<td>Yes</td>
<td>87</td>
<td>71.90%</td>
</tr>
<tr>
<td></td>
<td>No</td>
<td>34</td>
<td>28.10%</td>
</tr>
<tr>
<td>Eating vegan</td>
<td>Yes</td>
<td>16</td>
<td>13.22%</td>
</tr>
<tr>
<td></td>
<td>No</td>
<td>105</td>
<td>86.78%</td>
</tr>
</tbody>
</table>

Risk aversion was assessed using a Likert Scale ranging from one to ten, where one signals a strong aversion to risk, and ten indicates a high inclination towards risk-taking. The first question regarding risk tolerance was about participants' general tendency to take risks in their everyday lives. Participants' responses varied widely, displayed in Table 4, from one to ten, resulting in an average score of 5.47. This suggests that, overall, participants hold a fairly balanced view towards risk. However, the data does show a significant spread, with a standard deviation of 2.43 and a variance of 5.90 per response, implying substantial individual differences in risk tolerance. As for the responses to the second question, a similar trend was observed. The mean response hinted at a balanced view towards risk in terms of investment decisions, with an average score of 4.85. Yet, a standard deviation of 2.41 and a variance of 5.81 indicated individual variances in attitudes towards investment risks.

### Table 4: Descriptive statistics - risk preferences of the respondents

<table>
<thead>
<tr>
<th>Variable</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>SD</th>
<th>Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td>1</td>
<td>9.5</td>
<td>5.16</td>
<td>2.42</td>
<td>5.86</td>
</tr>
<tr>
<td>Risk life</td>
<td>1</td>
<td>10</td>
<td>5.47</td>
<td>2.43</td>
<td>5.90</td>
</tr>
<tr>
<td>Risk invest</td>
<td>1</td>
<td>9</td>
<td>4.85</td>
<td>2.41</td>
<td>5.81</td>
</tr>
</tbody>
</table>
Participants' perception of the potential of THIS™ was gauged using a Likert Scale, ranging from one to five, where one indicates low perceived potential and five signifies high potential. For the risk aspect, the scale was reversed, meaning a higher score represented lower perceived risk and vice versa. Participants rated the overall potential, market viability, practical feasibility, novelty, creativity, and associated risk of the idea. On average, the overall potential was deemed slightly above average, with a mean score of 3.92 as shown in Table 5. The practical feasibility and market viability received positive average ratings of 3.83 and 3.95, respectively. However, the novelty and risk aspects received middling scores with an average of about 2.93 and 2.94, respectively. Taking all factors into account, THIS™ was generally perceived slightly more positively, with an overall average score of 3.52. Individual responses per question varied by about a point depending on the specific aspect being rated, and an average variance of 1.05, indicates a range of individual views.

Table 5: Descriptive statistics - how respondents evaluated the idea

<table>
<thead>
<tr>
<th>Variable</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>SD</th>
<th>Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td>1</td>
<td>5</td>
<td>3.52</td>
<td>1.03</td>
<td>1.05</td>
</tr>
<tr>
<td>Feasibility</td>
<td>1</td>
<td>5</td>
<td>3.83</td>
<td>0.88</td>
<td>0.77</td>
</tr>
<tr>
<td>Market potential</td>
<td>2</td>
<td>5</td>
<td>3.95</td>
<td>0.84</td>
<td>0.70</td>
</tr>
<tr>
<td>Novelty creativity</td>
<td>1</td>
<td>5</td>
<td>2.93</td>
<td>1.01</td>
<td>1.01</td>
</tr>
<tr>
<td>Overall potential</td>
<td>1</td>
<td>5</td>
<td>3.93</td>
<td>0.90</td>
<td>0.80</td>
</tr>
<tr>
<td>Risk inverse</td>
<td>1</td>
<td>5</td>
<td>2.94</td>
<td>0.93</td>
<td>0.87</td>
</tr>
</tbody>
</table>

4.1.3. Moderating variables
This study investigated the factors that influenced the effect of emotions on investment decisions. Financial literacy was measured using a twelve-question single-choice quiz. For each correct answer, participants received a point, while incorrect answers didn't reduce their score. The results of this quiz are displayed in Tables 6 and 7. Participants, on average, achieved a score of 8.30, a figure close to Hanaki's (2022) average of 8.5. In the scope of this study, 75
per cent of participants scored ten points or less, and 25 per cent scored seven points or less. Table X showcases the distribution of the financial literacy quiz scores across various education levels. Participants with doctoral degrees recorded the highest scores. However, it's essential to note that this group was considerably smaller compared to others. Individuals with bachelor's or master's degrees ranked second and third in terms of highest average scores. It's important to recognize that these degrees could be in any field and may not necessarily require extensive financial knowledge. Still, showing the score distribution by education level is useful as it highlights the differences across varied educational backgrounds, providing a more detailed understanding of the data.

Table 6: Descriptive statistics - results of the financial literacy quiz

<table>
<thead>
<tr>
<th></th>
<th>Min</th>
<th>Q1</th>
<th>Mean</th>
<th>Q3</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2</td>
<td>7.00</td>
<td>8.31</td>
<td>10.00</td>
<td>12</td>
</tr>
</tbody>
</table>

Table 7: Descriptive statistics - comparison of financial literacy by education level

<table>
<thead>
<tr>
<th>Education level</th>
<th>Count</th>
<th>Min</th>
<th>Q1</th>
<th>Mean</th>
<th>Q3</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abitur or Matura</td>
<td>37</td>
<td>3</td>
<td>6.00</td>
<td>7.86</td>
<td>9.00</td>
<td>12</td>
</tr>
<tr>
<td>Bachelor</td>
<td>59</td>
<td>2</td>
<td>7.00</td>
<td>8.61</td>
<td>11.00</td>
<td>12</td>
</tr>
<tr>
<td>Master</td>
<td>15</td>
<td>4</td>
<td>7.50</td>
<td>8.33</td>
<td>10.50</td>
<td>12</td>
</tr>
<tr>
<td>Doctoral degree</td>
<td>1</td>
<td>11</td>
<td>11.00</td>
<td>11.00</td>
<td>11.00</td>
<td>11</td>
</tr>
<tr>
<td>Other</td>
<td>9</td>
<td>4</td>
<td>5.00</td>
<td>7.78</td>
<td>10.00</td>
<td>12</td>
</tr>
</tbody>
</table>

In the experiment, a seven-point Likert Scale was used to measure emotional expressivity, with one denoting strong disagreement and seven indicating strong agreement. Participants responded to four questions regarding their emotional expressivity, the results of which are shown in Table 8. On average, participants leaned towards an agreement with the statements, implying a moderate level of emotional expressivity, evidenced by an average score of 4.59. Small differences were noticed between the responses to different questions. On average, participants agreed most with the statement expressing that they experience their emotions very
intensely, as indicated by a mean score of 4.85. However, this was only marginally higher than the scores for other statements. Conversely, participants agreed least with the statement suggesting that their emotions are visible on their faces, as demonstrated by a lower average score of 4.28. Individual variations in responses ranged between 1.48 and 1.66 points depending on the statement, with a variance between 2.20 and 2.76 points. In conclusion, it's important to highlight that participants fully utilized the scale across all statements, as both the lowest and highest values were observed in the responses for each statement.

Table 8: Descriptive statistics - analysis of emotional expressivity

<table>
<thead>
<tr>
<th>Variable</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>SD</th>
<th>Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td>1</td>
<td>7</td>
<td>4.59</td>
<td>1.54</td>
<td>2.37</td>
</tr>
<tr>
<td>Emotionally expressive...</td>
<td>1</td>
<td>7</td>
<td>4.69</td>
<td>1.50</td>
<td>2.26</td>
</tr>
<tr>
<td>Emotions written in face…</td>
<td>1</td>
<td>7</td>
<td>4.28</td>
<td>1.48</td>
<td>2.20</td>
</tr>
<tr>
<td>Experience emotions strongly…</td>
<td>1</td>
<td>7</td>
<td>4.85</td>
<td>1.50</td>
<td>2.26</td>
</tr>
<tr>
<td>Body reacts strong to emotions</td>
<td>1</td>
<td>7</td>
<td>4.54</td>
<td>1.66</td>
<td>2.77</td>
</tr>
</tbody>
</table>

4.1.4. Main variables

Data on the factors influencing investment decisions, as well as the decisions themselves, was gathered using questionnaires. Facial expressions were monitored using TAWNY to detect changes. The analysis centred on particular emotions like anger and desire, as well as elements like valence, arousal, and affect. The study also looked at investment decisions made with varying information regarding the progress of the funding goal. True to our data collection approach, our sample consisted of 121 participants. Of these, 65 participants were informed halfway through the crowdfunding campaign that 25% of the funding goal had been met. The rest, 56 participants, were told at the same stage that 90% of the funding goal was achieved.

The Discrete Emotions Questionnaire (DEQ), paired with a Likert Scale from one to seven, was used to collect data on the emotions of anger and desire. A score of one indicated an
absence of the given emotion, while a seven indicated a strong presence of it. Participants noted their emotional responses while watching THIS™'s pitch video, and these results are presented in Table 9. Both anger and desire encompassed several related emotional items. The anger score included emotions such as anger, mad, pissed off, and rage. The average score was 1.19, indicating that participants generally did not feel anger while watching the pitch video. However, there were outliers, with anger reaching the scale's maximum score of seven. With a standard deviation of 0.68 points and an average variance of 0.48 points, it appears that anger was not a commonly reported emotion among participants. For desire, related emotions encompassed desire, longing, and wanting. The average score for desire was 3.41, suggesting variable experiences of desire among participants during the video. Compared to anger, the standard deviation for desire was higher, at 1.60 points, with a variance of 2.58 points, showing a wide range in the experience of desire. Notably, for the 'longing' item, the highest score recorded was six, indicating that the full scale was not utilized.

Table 9: Descriptive statistics - results of the DEQ

<table>
<thead>
<tr>
<th>Groups</th>
<th>Variable</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>SD</th>
<th>Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Anger</td>
<td>Average</td>
<td>1.00</td>
<td>5.75</td>
<td>1.19</td>
<td>0.68</td>
<td>0.48</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.00</td>
<td>7.00</td>
<td>1.30</td>
<td>0.91</td>
<td>0.83</td>
</tr>
<tr>
<td></td>
<td>Mad</td>
<td>1.00</td>
<td>5.00</td>
<td>1.12</td>
<td>0.52</td>
<td>0.27</td>
</tr>
<tr>
<td></td>
<td>Pissed off</td>
<td>1.00</td>
<td>5.00</td>
<td>1.23</td>
<td>0.73</td>
<td>0.53</td>
</tr>
<tr>
<td></td>
<td>Rage</td>
<td>1.00</td>
<td>6.00</td>
<td>1.12</td>
<td>0.56</td>
<td>0.31</td>
</tr>
<tr>
<td>Desire</td>
<td>Average</td>
<td>1.00</td>
<td>6.67</td>
<td>3.41</td>
<td>1.60</td>
<td>2.58</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.00</td>
<td>7.00</td>
<td>3.65</td>
<td>1.54</td>
<td>2.36</td>
</tr>
<tr>
<td></td>
<td>Longing</td>
<td>1.00</td>
<td>6.00</td>
<td>3.17</td>
<td>1.53</td>
<td>2.36</td>
</tr>
<tr>
<td></td>
<td>Wanting</td>
<td>1.00</td>
<td>7.00</td>
<td>3.42</td>
<td>1.74</td>
<td>3.03</td>
</tr>
</tbody>
</table>

TAWNY employed facial recognition and a machine learning algorithm to collect data on valence and arousal. It gathered data points every second, ranging from -1 (highly unpleasant}
or low arousal) to 1 (highly pleasant or high arousal). Furthermore, TAWNY captured participants' facial expressions for a few seconds without a stimulus before the video began to establish a baseline. This baseline was then subtracted from the collected data, ensuring the data only showed changes in emotional reactions caused by the video. For example, if someone displayed high valence and arousal before the video and these values stayed constant during the video, their valence and arousal would be reported as close to zero.

Table 10 presents the changes in valence and arousal, along with their variance during the video. On average, valence and arousal were neutral, leaning slightly towards pleasantness and moderate arousal. Valence had an average score of 0.016 and a standard deviation of 0.079, indicating that some participants strayed from the average score and experienced stronger feelings of pleasantness or unpleasantness. The range of extreme measures was from -0.186 to 0.229, indicating that the video triggered both negative and positive reactions. The extremes in arousal spread wider than in valence, ranging from -0.218 to 0.246, implying larger outliers since the standard deviation is smaller even with a wider spread. In conclusion, on average, participants maintained a relatively neutral emotional state during the pitch video, with outliers at both ends of the spectrum.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>SD</th>
<th>Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Valence</td>
<td>-0.19</td>
<td>0.23</td>
<td>0.02</td>
<td>0.08</td>
<td>0.01</td>
</tr>
<tr>
<td>Arousal</td>
<td>-0.22</td>
<td>0.25</td>
<td>0.01</td>
<td>0.06</td>
<td>0.00</td>
</tr>
<tr>
<td>Var Valence</td>
<td>0.00</td>
<td>0.03</td>
<td>0.01</td>
<td>0.01</td>
<td>0.00</td>
</tr>
<tr>
<td>Var Arousal</td>
<td>0.00</td>
<td>0.02</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Our experiment revolved around two investment decisions participants needed to make. Initially, all 121 participants decided without extra information about the funding status. Their decision was binary, either 'Yes' to invest or 'No' not to. If they chose 'Yes', they could decide how much to invest in increments of 250 ECU, 500 ECU, 750 ECU, or 1000 ECU. Table 11 shows the breakdown of these decisions. Of the 121 participants, 76 chose to invest, while the remaining 45 did not. The average investment across all participants was 342.98 ECU. But, if
we only consider the 76 who decided to invest, the average investment jumps to 546.05 ECU. A closer look at the data reveals a normal distribution pattern of investment amounts among those who invested, as shown in Table 12.

Table 11: Descriptive statistics - investment decisions without funding status

<table>
<thead>
<tr>
<th>Investment Decision – No Funding Goal</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes</td>
<td>76</td>
</tr>
<tr>
<td>No</td>
<td>45</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Investment</th>
<th>Min</th>
<th>Q1</th>
<th>Mean</th>
<th>Q3</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>250 ECU</td>
<td>17</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>500 ECU</td>
<td>36</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>750 ECU</td>
<td>15</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1000 ECU</td>
<td>8</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

n 121

Table 12: Descriptive statistics - comparison in the amount invested with no funding status

<table>
<thead>
<tr>
<th>Investment</th>
<th>Min</th>
<th>Q1</th>
<th>Mean</th>
<th>Q3</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Among everybody</td>
<td>0</td>
<td>0</td>
<td>342.98</td>
<td>500</td>
<td>1000</td>
</tr>
<tr>
<td>Only those who invested</td>
<td>250</td>
<td>500</td>
<td>546.05</td>
<td>750</td>
<td>1000</td>
</tr>
</tbody>
</table>

After the first investment decision was made without any funding status information, we split the participants into two groups randomly. Results are shown in Tables 13 and 14. The first group, with 56 people, was informed halfway through the crowdfunding campaign that the funding goal was 90% reached. In this group, after receiving the update, a small increase in investment activity was seen, with three more people deciding to invest. This increased the number of investors from 34 to 37. Before the funding status update, the average investment was 343.75 ECU, with investors contributing an average of 566.18 ECU. After being told that 90% of the funding goal was achieved, the average investment rose to 397.32 ECU, and the mean amount among investors increased to 601.35 ECU. Hence, the extra information resulted in a rise in both the number of investors and the amount invested.
Table 13: Descriptive statistics - investment decisions with funding status 90

<table>
<thead>
<tr>
<th>Investment Decision – Funding Goal 90</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes</td>
<td>37</td>
</tr>
<tr>
<td>No</td>
<td>19</td>
</tr>
<tr>
<td>250 ECU</td>
<td>7</td>
</tr>
<tr>
<td>500 ECU</td>
<td>13</td>
</tr>
<tr>
<td>750 ECU</td>
<td>12</td>
</tr>
<tr>
<td>1000 ECU</td>
<td>5</td>
</tr>
<tr>
<td>n</td>
<td>56</td>
</tr>
</tbody>
</table>

Table 14: Descriptive statistics - comparison in the amount invested between no funding status and funding status 90

<table>
<thead>
<tr>
<th>Investment Before/After Funding Goal 90</th>
<th>Min</th>
<th>Q1</th>
<th>Mean</th>
<th>Q3</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Before: Among everybody</td>
<td>0</td>
<td>0</td>
<td>343.75</td>
<td>500</td>
<td>1000</td>
</tr>
<tr>
<td>After: Among everybody</td>
<td>0</td>
<td>0</td>
<td>397.32</td>
<td>750</td>
<td>1000</td>
</tr>
<tr>
<td>Before: Only who invested</td>
<td>250</td>
<td>500</td>
<td>566.18</td>
<td>750</td>
<td>1000</td>
</tr>
<tr>
<td>After: Only who invested</td>
<td>250</td>
<td>500</td>
<td>601.35</td>
<td>750</td>
<td>1000</td>
</tr>
</tbody>
</table>

The second group, made up of 65 people, was informed midway through the crowdfunding campaign that the funding goal was only 25% reached. The full results of their investment decisions are displayed in Tables 15 and 16. In the first investment decision, the average investment for those in the 25% group who decided to invest was 529.76 ECU, less than the average of 566.18 ECU in the 90% group. After finding out that only 25% of the funding goal had been reached, the number of investors fell from 42 to 34. This decrease led to a drop in the average investment amount from 342.31 ECU to 280.77 ECU. However, if we only look at those who invested, the average investment amount slightly rose from 529.76 ECU to 536.76 ECU. This shows that the people who kept investing, despite less of the funding goal being
achieved, slightly upped their investment amounts, showing a minimally stronger commitment to their investment.

Table 15: Descriptive statistics - investment decisions with funding status 25

<table>
<thead>
<tr>
<th>Investment Decision – Funding Goal 25</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes</td>
<td>34</td>
</tr>
<tr>
<td>No</td>
<td>31</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Investment Before/After Funding Goal 25</th>
<th>Min</th>
<th>Q1</th>
<th>Mean</th>
<th>Q3</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Before: Among everybody</td>
<td>0</td>
<td>0</td>
<td>342.31</td>
<td>500</td>
<td>1000</td>
</tr>
<tr>
<td>After: Among everybody</td>
<td>0</td>
<td>0</td>
<td>280.77</td>
<td>500</td>
<td>1000</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Investment Before/After Funding Goal 25</th>
<th>Min</th>
<th>Q1</th>
<th>Mean</th>
<th>Q3</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Before: Only those who invested</td>
<td>250</td>
<td>250</td>
<td>529.76</td>
<td>750</td>
<td>1000</td>
</tr>
<tr>
<td>After: Only those who invested</td>
<td>250</td>
<td>250</td>
<td>536.76</td>
<td>750</td>
<td>1000</td>
</tr>
</tbody>
</table>

4.2. Statistical Analysis

In this second part of the analysis chapter, I will present the results from the statistical analysis performed using R. The process involved verifying the reliability and validity of the data, examining the correlation between different data points, and finally, testing the hypotheses proposed in the theoretical framework.

4.2.1. Reliability and Validity

Assessing the reliability and validity of a measurement tool is essential for ensuring the accuracy of the conclusions drawn from the data. Validity refers to how well the tool measures
what it's supposed to measure, while reliability gauges the consistency of the tool's measurements (Tavakol and Dennick 2011). Cronbach’s alpha is commonly used to assess that. It ranges from zero to one, with a higher Cronbach's alpha signifying lower random error in the measurement tool. Typically, a Cronbach's alpha value above 0.70 is considered acceptable, indicating reliable measurement. However, an alpha value over 0.90 may not always be desirable as it could suggest redundancy in the tool or an excessively lengthy measure (Tavakol and Dennick 2011). Another method to assess the reliability and validity of a measurement tool is the computation of the Average Variance Extracted (AVE). An AVE analysis examines whether a construct captures more unique information and thus explains more data variability compared to other constructs (Zaiţ and Bertea 2011). For the measure to be deemed acceptable, the AVE score should exceed the threshold of 0.50.

Table 17 provides the calculated results for items measured with different questionnaires during the experiment, to test their reliability and validity. Idea evaluation and anger were not included in the calculations because the assumptions of Cronbach’s alpha were not met. Anger was excluded as one assumption of Cronbach’s alpha is normality (Field et al. 2012), and anger's values are highly skewed to the right. Idea evaluation was left out as Cronbach’s alpha is used to validate existing questionnaires, and the questions for idea evaluation were created uniquely to investigate idea evaluation. Consequently, the alphas were calculated for desire, emotional expressivity, mood, and risk aversion. The values for all items are above the threshold of 0.70 and below the recommended upper limit of 0.90 (Tavakol and Dennick 2011), so we can assume the scales of desire, emotional expressivity, mood, and risk aversion are valid and reliable. However, the score for desire should be interpreted with some caution as its data is barely normally distributed but is not skewed in any particular direction. In addition, all variables scored above the threshold of 0.50 in the AVE, which further substantiates the reliability and validity of the data.

Table 17: Statistical analysis - testing for reliability & validity

<table>
<thead>
<tr>
<th>Variable</th>
<th>Cronbach’s Alpha</th>
<th>AVE</th>
<th>Number of Items</th>
</tr>
</thead>
<tbody>
<tr>
<td>Emotional Expressivity</td>
<td>0.86</td>
<td>0.62</td>
<td>4</td>
</tr>
<tr>
<td>Anger</td>
<td>0.79</td>
<td>0.61</td>
<td>4</td>
</tr>
<tr>
<td>Desire</td>
<td>0.89</td>
<td>0.75</td>
<td>3</td>
</tr>
<tr>
<td>Mood</td>
<td>0.84</td>
<td>0.65</td>
<td>3</td>
</tr>
</tbody>
</table>
The Pearson correlation coefficient is frequently employed to assess the correlation between two variables. Though the only prerequisite of Pearson’s correlation is that data are interval, the significance of the correlation coefficients demands that the data for both variables are normally distributed (Field et al. 2012). As such, anger is omitted from Pearson’s correlation matrix. The correlation matrix output ranges from -1 to 1. Values from 0.5 to 1 denote a strong correlation, values from 0.30 to 0.5 indicate a moderate correlation, and values below 0.3 suggest a weak correlation. The same correlation interpretation applies to negative values, however, it signifies strong to weak negative relationships compared to positive ones. Nonetheless, the thresholds for interpreting the correlation matrix are subject to debate and can differ among researchers (Schober et al. 2018). Table 18 displays the correlation coefficients of variables gathered during the experiment. The most substantial correlation between variables is observed between valence and arousal, with a moderate correlation. Additionally, idea evaluation and desire moderately correlate. Most variables, however, exhibit a weak correlation with each other, suggesting that they are predominantly independent of one another.

*Table 18: Statistical analysis - Pearson correlation matrix*

<table>
<thead>
<tr>
<th></th>
<th>Valence</th>
<th>Arousal</th>
<th>Mood</th>
<th>FL total</th>
<th>EE</th>
<th>Risk</th>
<th>IE overall</th>
<th>Desire</th>
</tr>
</thead>
<tbody>
<tr>
<td>Valence</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Arousal</td>
<td>0.39</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mood</td>
<td>-0.05</td>
<td>0.09</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FL total</td>
<td>0.17</td>
<td>-0.01</td>
<td>0.08</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EE</td>
<td>0.11</td>
<td>0.00</td>
<td>-0.03</td>
<td>-0.25</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Risk</td>
<td>0.12</td>
<td>-0.06</td>
<td>0.11</td>
<td>0.27</td>
<td>-0.22</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IE overall</td>
<td>0.07</td>
<td>0.06</td>
<td>-0.07</td>
<td>-0.06</td>
<td>0.20</td>
<td>-0.07</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>Desire</td>
<td>0.15</td>
<td>0.00</td>
<td>0.07</td>
<td>0.10</td>
<td>0.06</td>
<td>0.22</td>
<td>0.34</td>
<td>1.00</td>
</tr>
</tbody>
</table>
4.2.2. Analysing research question one.

The research question guiding this study is: How does economic knowledge impact the role of emotions in investment decisions for retail investors in crowdfunding? To address this, I formulated Hypotheses H1 and H2 which I test and analyse in this subsection. The first hypothesis examines the influence of emotions on the investment decision. I believe that it's crucial to first analyse the emotions' impact on the investment decision before delving into the effect of economic knowledge, hence establishing a fundamental understanding. H2 then tests the moderating effects of economic knowledge as measured through the financial literacy quiz.

To test these hypotheses, I performed logistic regressions in R. This methodology is suitable as the outcome variable is binary, and the hypothesis tests whether an investment takes place (1) or not (0). Logistic regression assumes linearity, independence of errors, and no multicollinearity (Field et al. 2012). To ensure these assumptions, I conducted tests for multicollinearity and linearity of the logit. Although I report the test results here, the full tables will be provided in the appendix due to space constraints. For each tested hypothesis, a summary table will be reported including predictors, odds ratio, confidence intervals, and p-value. The odds ratio reflects the change in odds resulting from a unit change in the predictor, defined as the likelihood of an event occurring divided by the probability of that event not occurring (Field et al. 2012). The confidence interval in a logistic regression represents a range of plausible values for the coefficient of a variable based on the data used to estimate the model. In business research, a 95 per cent confidence interval is common, hence a p-value below 0.05 is deemed statistically significant. Each model will consist of the dependent variable 'investment decision' and the control variables 'risk aversion' and 'idea evaluation.' The models will differ based on the independent variable predicting the investment decision. Consequently, I split the first hypothesis into three parts analysing the effects of desire, anger, and affect on the investment decision, respectively.

The findings about the influence of desire on the investment decision are displayed in Table 19. The p-value of desire, suggests that the positive influence of desire on the investment decision is highly significant. Further, the odds ratio of desire implies that with each one-unit increase in desire, the odds of making an investment decision are 1.72 times greater, holding all else constant. Moreover, idea evaluation has a significant positive impact on the investment decision. The results of testing the model for multicollinearity suggest that none exists as all values are close to one. It's only considered problematic if the value is either above 5 or 10 (Field et al. 2012). The test for the linearity of the logit also returned positive, implying that
the outcome is a linear function of the predictor variables (Field et al. 2012), thereby validating the model. To conclude, as the model suggests a significant relationship between desire and the investment decision, and as all assumptions about logistic regressions are met, **H1a is accepted.**

**Table 19: Statistical analysis - results from logistic regression for H1a**

<table>
<thead>
<tr>
<th>Predictors</th>
<th>Odds Ratios</th>
<th>CI</th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>0.00</td>
<td>0.00 – 0.05</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Desire</td>
<td>1.72</td>
<td>1.24 – 2.44</td>
<td>0.002</td>
</tr>
<tr>
<td>Risk</td>
<td>1.00</td>
<td>0.82 – 1.22</td>
<td>0.987</td>
</tr>
<tr>
<td>IE overall</td>
<td>4.34</td>
<td>1.82 – 11.63</td>
<td>0.002</td>
</tr>
</tbody>
</table>

Observations 121

R² Tjur 0.249

The same analysis was repeated, replacing 'desire' with 'anger'. The results, presented in Table 20, suggest a significant relationship between anger and investment decision. However, the results indicate a significantly negative relationship between anger and the investment decision. The odds ratio of 0.25 implies that with each unit increase in anger, the odds of making an investment decision are four times less likely, all else being equal. Once again, idea evaluation has a statistically significant positive effect on the investment decision, while risk preference does not. Moreover, the model is valid as tests suggest there is no multicollinearity, and the linearity of the logit is confirmed. However, as Hypothesis H1b suggests that anger has a positive effect on the investment decision, **H1b is rejected**, because the results indicate that anger has a statistically significant negative effect on the investment decision.
To conclude the testing of the effect of emotion on the investment decision, Hypothesis H1c examines the effect of affect, which is computed as the variance of arousal multiplied by valence, on the investment decision. Unlike desire and anger, affect does not have a statistically significant influence on the investment decision as shown in Table 21. Initially, affect had an odds ratio of infinity and a confidence interval ranging from negative infinity to infinity because the values of affect are so small. Therefore, I multiplied affect by 1000 so the table could be better visualized. I analysed before and after the manipulation of affect to ensure that all other values, apart from the confidence interval and odds ratio of affect, remained the same. In addition, idea evaluation continues to have a statistically significant positive effect on the investment decision, while risk preference does not. Moreover, the model is valid as tests suggest no multicollinearity and the linearity of the logit is confirmed. To conclude, Hypothesis **H1c is rejected** as no statistically significant effect of affect on the investment decision is found.

### Table 20: Statistical analysis - results from logistic regression for H1b

<table>
<thead>
<tr>
<th>Predictors</th>
<th>Odds Ratios</th>
<th>CI</th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>0.00</td>
<td>0.00 – 0.10</td>
<td>0.002</td>
</tr>
<tr>
<td>Anger</td>
<td>0.25</td>
<td>0.09 – 0.56</td>
<td>0.002</td>
</tr>
<tr>
<td>Risk</td>
<td>1.14</td>
<td>0.94 – 1.39</td>
<td>0.987</td>
</tr>
<tr>
<td>IE overall</td>
<td>8.02</td>
<td>3.22 – 23.45</td>
<td>0.002</td>
</tr>
</tbody>
</table>

Observations 121

R² Tjur 0.259
Table 21: Statistical analysis – results from logistic regression for H1c

<table>
<thead>
<tr>
<th>Predictors</th>
<th>Odds Ratios</th>
<th>CI</th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>0.00</td>
<td>0.00 – 0.06</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Affect</td>
<td>1.94</td>
<td>0.82 – 5.71</td>
<td>0.182</td>
</tr>
<tr>
<td>Risk</td>
<td>1.08</td>
<td>0.90 – 1.30</td>
<td>0.425</td>
</tr>
<tr>
<td>IE overall</td>
<td>5.74</td>
<td>2.51 – 14.95</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

Observations 121

R² Tjur 0.192

The second hypothesis aims to analyse the moderating effect of financial literacy on the influence of desire, anger, and affect respectively on the investment decision. Consequently, each of the three models analysed in H1 was expanded by the interaction effect between financial literacy and the respective independent variable. Again, idea evaluation and risk preference were added as control variables. H2a analysed the moderating effect of financial literacy on desire in investment situations, with the results displayed in Table 22. After including the interaction effect, desire no longer has a significant impact on the investment decision, nor does financial literacy or the interaction effect between the two. In the model, the interaction effect of desire and financial literacy has an odds ratio of 0.93, suggesting a slightly negative influence, all other factors being equal. However, the confidence interval of 0.80-1.07 includes 1 and therefore implies that the slightly negative effect is not statistically significant. Nonetheless, idea evaluation still has a statistically significant positive effect on the investment decision, with an odds ratio of 5.05 and a p-value of 0.001. In conclusion, **H2a is rejected** as financial literacy does not have a statistically significant moderating effect on the influence of desire on the investment decision. H2a:
Table 22: Statistical analysis - results from logistic regression for H2a

<table>
<thead>
<tr>
<th>Predictors</th>
<th>Odds Ratios</th>
<th>CI</th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>0.00</td>
<td>0.00 – 0.01</td>
<td><strong>0.001</strong></td>
</tr>
<tr>
<td>Desire</td>
<td>3.25</td>
<td>0.98 – 13.30</td>
<td>0.073</td>
</tr>
<tr>
<td>FL total</td>
<td>1.46</td>
<td>0.92 – 2.51</td>
<td>0.132</td>
</tr>
<tr>
<td>Risk</td>
<td>0.96</td>
<td>0.77 – 1.18</td>
<td>0.679</td>
</tr>
<tr>
<td>IE overall</td>
<td>5.05</td>
<td>2.06 – 14.00</td>
<td><strong>0.001</strong></td>
</tr>
<tr>
<td>Desire * FL total</td>
<td>0.93</td>
<td>0.80 – 1.07</td>
<td>0.314</td>
</tr>
</tbody>
</table>

Observations 121

R² Tjur 0.273

In analysing H2b, desire was replaced with anger. Table 23 shows the results of the adjusted model, and similarly to the model testing H2a, financial literacy has no statistically significant moderating effect on the influence of anger on the investment decision. With an odds ratio of 0.91, it suggests a slightly negative relationship, but again, the confidence interval includes 1, suggesting no statistical significance. Interestingly, the inclusion of the interaction effect between financial literacy and anger impacts the main effect of anger on the investment decision, as the effect is no longer significant. Consistent with the model testing H1b, the positive statistical significance of idea evaluation is confirmed with an odds ratio of 9.07, a confidence interval not including 1, and a p-value less than 0.001. Furthermore, risk preference does not have a statistically significant influence on the investment decision. This leads to the rejection of H2b, as financial literacy has no statistically significant moderating effect on the influence of anger on the investment decision.
Table 23: Statistical analysis - results from logistic regression for H2b

<table>
<thead>
<tr>
<th>Predictors</th>
<th>Odds Ratios</th>
<th>CI</th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>0.00</td>
<td>0.00 – 0.09</td>
<td>0.005</td>
</tr>
<tr>
<td>Anger</td>
<td>0.50</td>
<td>0.01 – 13.00</td>
<td>0.708</td>
</tr>
<tr>
<td>FL total</td>
<td>1.31</td>
<td>0.77 – 2.21</td>
<td>0.306</td>
</tr>
<tr>
<td>Risk</td>
<td>1.07</td>
<td>0.87 – 1.33</td>
<td>0.518</td>
</tr>
<tr>
<td>IE overall</td>
<td>9.07</td>
<td>3.54 – 27.73</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Anger * FL total</td>
<td>0.91</td>
<td>0.60 – 1.43</td>
<td>0.671</td>
</tr>
</tbody>
</table>

Observations 121

R² Tjur 0.277

Finally, the moderating effect of financial literacy on affect's influence on the investment decision was analysed and is shown in Table 24. Similar to previous results, financial literacy does not have a statistically significant moderating effect on any of the predictors. Notably, while the inclusion of the moderating effect of financial literacy on desire and anger, respectively, rendered the main effects of both non-significant, here the main effect remains non-significant and consistent with the model for H1c. Affect has been treated the same as for H1c for a more accurate display in the summary table. As before, idea evaluation is highly statistically significant and positively impacts the investment decision, whereas risk does not have a significant effect. In conclusion, **H2c is rejected** as financial literacy does not have a statistically significant moderating effect on the influence of affect on the investment decision.
4.2.3. Analysing research question two

To analyse my second research question, "How does the funding status impact the investment decisions of retail investors?", a different analytical approach than logistic regressions was required. For hypotheses H3a and H3b, a comparison of two means was necessary. To compare the means of the amount invested, I conducted a Wilcoxon signed rank test for both hypotheses. While the common method to analyse two means from the same participant involves using a dependent t-test, in this case, the values for the investment amount are not normally distributed. Therefore, the robustness of a Wilcoxon signed rank test to non-normality was required (Field et al. 2012).

Hypothesis H3a aimed to analyse whether the investment amount is statistically significantly higher after learning that the funding goal has been 90 per cent reached halfway through the crowdfunding campaign compared to not knowing the funding status. Given that, in both instances, some participants did not invest at all and the scale is 0, 250, 500, 750, and 1,000, the data is skewed to the right necessitating a Wilcoxon signed rank test and the results presented in Table 25. Based on the results of the analysis, individuals invested significantly more after knowing the funding status compared to before, with a p-value of 0.047. Figure 5
depicts the distribution of the amounts invested with and without knowledge of the funding status, indicating that the median investment was higher when the funding status was known. Additionally, the effect size of the Wilcoxon signed-rank test is 0.426, indicating a medium to a large effect (Field et al. 2012). Based on the results outlined, **H3a is accepted**, indicating that knowledge of a campaign reaching 90 per cent of its funding goal halfway through the crowdfunding campaign statistically significantly increases the amount invested.

**Table 25: Statistical analysis - results from Wilcoxon signed-rank test for H3a**

<table>
<thead>
<tr>
<th>W</th>
<th>p value</th>
<th>rc</th>
</tr>
</thead>
<tbody>
<tr>
<td>135.5</td>
<td><strong>0.047</strong></td>
<td>0.426</td>
</tr>
</tbody>
</table>

**Figure 5: Comparison amount invested, funding status 90 - no funding status**

Hypothesis 3b aimed to analyse whether the investment amount is statistically significantly lower after learning that the funding goal has been 25 per cent reached halfway through the crowdfunding campaign compared to not knowing the funding status. As previously mentioned, the data for the amount invested is not normally distributed, and a Wilcoxon signed-rank test was conducted with the results displayed in Table 26. The results once again indicate statistical significance, with a p-value of 0.019, suggesting that people invested significantly less after learning that the funding goal had only reached 25 per cent. Figure 6 displays that the median investment amount is similar in both scenarios. However, during the descriptive
analysis, it was observed that fewer people invested in this scenario after learning about the funding status. Furthermore, the effect size of the Wilcoxon signed rank test is -0.426, indicating a medium to large effect. In conclusion, **H3b is accepted**, indicating that participants invested statistically significantly less after learning that only 25 per cent of the funding goal had been reached halfway through the crowdfunding campaign.

*Table 26: Statistical analysis - results from Wilcoxon signed-rank test for H3b*

<table>
<thead>
<tr>
<th>W</th>
<th>p value</th>
<th>rc</th>
</tr>
</thead>
<tbody>
<tr>
<td>116.5</td>
<td>0.019</td>
<td>-0.426</td>
</tr>
</tbody>
</table>

*Figure 6: Comparison amount invested, funding status 25 - no funding status*

Hypothesis H3c analysed whether the influence of desire on the investment decision is stronger after learning about the funding status being 25 per cent compared to not knowing the funding status. To examine H3c, a linear mixed-effects model was employed to analyse the effect of desire for each participant, once before knowing the funding status and once afterwards. The results are displayed in Table 27, and according to the analysis, the interaction effect of desire and the information on the funding status has a statistically significant negative relationship, with a p-value of 0.045 and an estimate of -0.07. This means the funding status of 25 per cent significantly reduces the influence of desire on investment decisions. Still, the positive main effect of desire on the investment decision is highly significant, with a p-value of less than
0.001. Additionally, Figure 7 displays the interaction effect of desire and knowledge of the funding status, showing that the slope of desire is flatter when participants are aware of the funding status compared to when they did not know, showing a weaker effect of desire. In conclusion, **H3c is rejected**, indicating that the information about the funding status being 25 per cent reached halfway through the crowdfunding campaign statistically significantly negatively moderates the influence of desire on the investment decision.

Table 27: Statistical analysis - results of linear mixed-effects model

<table>
<thead>
<tr>
<th>Predictors</th>
<th>Estimates</th>
<th>CI</th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>0.00</td>
<td>-0.22 – 0.41</td>
<td>0.561</td>
</tr>
<tr>
<td>Desire</td>
<td>0.15</td>
<td>0.07 – 0.24</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Info25</td>
<td>0.12</td>
<td>-0.13 – 0.36</td>
<td>0.364</td>
</tr>
<tr>
<td>Desire * Info25</td>
<td>-0.07</td>
<td>-0.13 - -0.00</td>
<td>0.045</td>
</tr>
</tbody>
</table>

**Random Effects**

- σ²: 0.07
- τ00 Token: 0.15
- ICC: 0.69
- N Token: 65

Observations: 130

Marginal R² /Conditional R²: 0.137 / 0.731

Figure 8 showcases the theoretical framework, illustrating all the hypotheses tested. It reveals that emotions such as desire and anger exert a statistically significant influence on investment decisions. However, core affect and the moderating impact of financial literacy do not significantly influence these decisions. Moreover, the funding status significantly affects the invested amount in two distinct ways: if the funding goal is 90 per cent achieved, more ECUs are invested, while a funding status of only 25 per cent leads to fewer ECUs being invested. Furthermore, it is notable that desire has a statistically significant negative moderating effect on investment decisions.
Figure 7: Difference of desire's influence on the investment decision in the model for H3c

Figure 8: Theoretical framework with significant results marked

** p < 0.05
4.2.4. Explorative Analysis

In addition to analysing my research questions and relevant hypotheses, I also examined the main effect of financial literacy on investment decisions and investment amounts. I conducted this analysis in three scenarios: without any funding status information, with 90 per cent funding status, and with 25 per cent funding status. This analysis is interesting because it explores whether financial literacy has a significant influence on investment decisions, regardless of the emotional factors and funding status. To maintain the focus and conciseness of my master's thesis, most of the analysis tables can be found in the appendix. I used logistic regressions to analyse the main effect of financial literacy on investment decisions and linear regressions to analyse its effect on investment amounts. In all models, the variables risk preference and idea evaluation were included as control variables.

When analysing the impact of financial literacy without any funding status information, it was found to have no statistical significance on investment decisions. However, financial literacy had a statistically significant positive effect on the amount invested, with a p-value of 0.017. Next, I divided the sample of 121 participants into two groups based on the funding information they received. Among the 56 participants who learned that the funding goal had been reached by 90 per cent, financial literacy had no statistically significant impact on either investment decisions or investment amounts after considering the funding status. However, when examining the data of the 65 participants who received the information that the funding goal was only 25 per cent achieved, financial literacy had a statistically significant positive effect on both investment decisions and investment amounts. This suggests that as financial literacy increases by one unit, the likelihood of making an investment and the amount invested also increase, particularly in the scenario where the funding goal is 25 per cent reached. Table 28 provides the corresponding p-values for financial literacy in all models.
Table 28: Statistical analysis - summary table of all p values of financial literacy as main effect

<table>
<thead>
<tr>
<th>Financial literacy</th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Investment decision – no funding status</td>
<td>0.101</td>
</tr>
<tr>
<td>Investment amount – no funding status</td>
<td>0.017</td>
</tr>
<tr>
<td>Investment decision – funding status 90</td>
<td>0.459</td>
</tr>
<tr>
<td>Investment amount – funding status 90</td>
<td>0.736</td>
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<tr>
<td>Investment decision – funding status 25</td>
<td>0.008</td>
</tr>
<tr>
<td>Investment amount – funding status 25</td>
<td>0.020</td>
</tr>
</tbody>
</table>
5. Discussion

In the discussion section, I intend to separately address both research questions, linking the results with relevant literature and my insights. Further, I discuss both theoretical and practical implications, as well as the limitations and suggestions for future research.

5.1. Answering the first research question
The first research question focused on the impact of financial literacy on the effect of emotions on investment decisions. Initially, the influence of emotions on investment decisions was studied to better understand how they dictate these decisions and subsequently examined how financial literacy might moderate this influence. As the influence of emotions on decision-making is an emerging research area (Lerner et al. 2015), its role in the specific context of investment decisions is relatively unexplored. However, Aliya and Bansal (2018) proposed that emotions significantly shape investment decisions. To scrutinize this assertion, I proposed hypothesis H1. The results confirmed that both self-reported desire and anger significantly influence investment decisions. Starting with desire, a discrete emotion that has not been extensively studied in the context of investment decisions, the results showed that it statistically increases the likelihood of an investment occurrence. Desire is known to trigger impulsive purchases (Rani 2014), which can subvert rational behaviour and lead to poor judgment (Morse 2006). While it's hard to deem investing in a crowdfunding project as right or wrong due to numerous influencing factors, it's plausible that the positive effect of desire led some participants to make impulsive investments without much forethought. While this assertion can't be made definitively due to potential other causes, it aligns with existing literature, and I propose it is likely one of several unstudied influences leading to such behaviour.

Contrary to my hypothesis, anger had a statistically significant negative impact on the investment decision. Given literature suggests that anger leads to riskier investment behaviour (Gambetti and Giusberti 2012) and reduces the time spent gathering relevant investment information (Wynes 2021), I expected anger to increase the likelihood of investment. However, in the study, participants anger led to fewer investments. I believe the deviation from previous findings might be due to the contextual difference: in this study, we questioned the emotion of anger in response to the pitch video, while prior studies focused on general states of anger. As such, assumptions based on previous findings may not have been suitable for this experimental setting. I propose that a more fitting context for examining anger would be to treat it as a
negative evaluation of the stimulus, thereby indicating disapproval of the product or the company.

Core affect did not exhibit a statistically significant influence on investment decisions. While literature suggests that positive affect leads individuals to perceive something more favourably than it is (Finucane et al. 2000), it didn't substantially alter the investment behaviour in this experiment. The affect data used for the analysis was gathered via TAWNY's facial recognition, which might not have been ideal for this analysis. Given that automatic emotion measurement isn't entirely accurate and relies on emotional expressivity (Mollahosseini et al. 2019). I suspect that if affect had been measured through the self-reported PANAS questionnaire from Watson et al. (1988), the data would have differed from TAWNY’s results. Furthermore, defining affect as the product of arousal variance and valence might not accurately represent affect. These factors may explain why affect didn't influence investment decisions, but it's also entirely possible that the outcome would remain unchanged even if affect were measured and constructed differently.

Based on these findings, I was able to investigate my first research question regarding the moderating effect of financial literacy, as a measure of economic knowledge, on the influence of emotions on investment decisions. Separate models in hypothesis H2 analyzed this moderating effect on the independent variables examined in H1. As the moderating effect of financial literacy on emotions in investment decisions remains under-studied, I grounded my hypothesis on the general characteristics of financial literacy. Financial literacy has been identified as promoting more rational investment behaviour (Baker et al. 2018) by reducing behavioural biases (Takeda et al. 2013) and fostering a better understanding of one's emotions during investment scenarios (Hadi 2017). Consequently, I hypothesized that financial literacy would likely moderate the influence of emotions. However, the results of H2 contradicted this belief. In all three models, the interaction term between the predictor and financial literacy lacked statistical significance. Therefore, financial literacy didn't regulate the influence of emotions in the investment scenario created.

This would lead to the conclusion that financial literacy has no moderating effect on emotions in investment decisions, but there are other factors to consider. Interestingly, including the interaction between the predictor and financial literacy in the logistic models of H1 resulted in neither desire nor anger being statistically significant anymore. One possible explanation could be the suppression effect, which reduces the relationship between the independent and
dependent variables when a mediator is included (MacKinnon et al. 2000). Additionally, the inclusion of the interaction term increased the likelihood of multicollinearity within the models, thereby reducing the reliability of the regression models (Daoud 2017). While the correlation between, for example, desire and financial literacy are very weak (below 0.10), the inclusion of the interaction term could still induce some multicollinearity. In conclusion, this study could not definitively establish the effect of financial literacy on the moderation of emotions in investment situations.

Nevertheless, the study led to intriguing findings. I conducted an exploratory study investigating the primary effect of financial literacy on investment decisions and investment amounts, yielding significant results. Financial literacy significantly increased the amount participants invested. This pattern aligns with existing literature, which suggests that individuals with higher financial literacy scores invest more frequently and exhibit greater confidence in their investments (Kumar 2020). In the experiment, I believe an avenue to identify this confidence is by analyzing who invested more money, a trend seen among respondents with higher financial literacy. Moreover, within the group that reported a 25 per cent funding status, financial literacy had a significant positive influence on both investment decisions and investment amounts. I believe a correlation can be drawn here with the tendency of financially literate individuals to act based on their own beliefs and remain less influenced by the behaviour of others (Nieddu and Pandolfi 2020). This might be because those who are more knowledgeable are likely aware that they won't lose their money if the funding goal isn't reached; in such cases, the only loss they incur is the financial flexibility that comes with locking their money into a project that yields no return.

In conclusion, while the analysis didn't affirm a moderating effect of financial literacy, it revealed other facts relevant to this study. The influence of anger on investment decisions was further substantiated and expanded upon by the finding that if individuals experience anger from the investment stimuli, it decreases the likelihood of investment. Further, this thesis contributed to a better understanding of the role of desire in investment decisions, particularly as the connection between desire and investment decisions has not been widely studied. Also, the study confirmed existing knowledge about financial literacy. Financial literacy increased the amounts invested and, especially in situations of high uncertainty (like a low funding status), financially literate individuals were more likely to invest, and also to invest more. An explanation for this might be because those people more likely were aware that they wouldn't lose the money invested if the crowdfunding campaign wasn't successful.
5.2. Answering the second research question

The second research question examined the impact of funding status and its influence on individuals' investment behaviour. Participants were divided into two groups, with one group learning that 25 per cent of the funding goal had been achieved halfway through the crowdfunding campaign, and the other group learning it was at 90 per cent. I based the first hypothesis on knowledge about herding behaviour (Vulkan et al. 2016) and proposed that individuals would invest more upon learning about a 90 per cent funding status. This assumption was confirmed through a Wilcoxon signed rank test, which showed that significantly more people invested in this scenario. One reason for this could be the reinforcement model (Cordova et al. 2015), as people might form their opinions based on others' behaviour. In this context, an investment from one person could lead to an investment from another. Therefore, I believe that for some potential investors, the funding status might signal the quality of the project. Besides being driven by behavioural biases, some investors might have invested more because they liked the product and wanted to ensure the project's realization after learning about the funding status.

In addition to examining herding behaviour when the funding goal is nearly reached, I also explored whether the opposite effect occurs in a scenario where the funding goal is unlikely to be achieved. Existing literature suggests that crowdfunding projects that start slowly often struggle to reach their funding goals (Colombo et al. 2015). This study supports that assertion, as people who learned about a funding status of 25 per cent invested significantly less than they did before knowing the funding status. A potential reason for this is that people tend to invest more as the target end goal nears (Kuppuswamy and Bayus 2017), which isn't the case in this scenario. In addition, participants' behaviour with a low funding status aligns with actual data about crowdfunding projects. Up to 2013, crowdfunding projects that failed to secure sufficient funding raised, on average, only about ten per cent of their funding goal (Mollick 2014). While this can't be attributed solely to low funding status, I believe that funding status is a significant factor, as indicated by the experiment's results.

Lastly, this master's thesis examined the role of desire in the investment decision when 25 per cent of the funding goal had been achieved. While the role of desire, when something seems unlikely, hasn't been studied extensively, I proposed that desire would exert a stronger influence among those who chose to invest, even though a successful crowdfunding campaign seemed improbable. Following the analysis, I rejected this hypothesis because the funding status had a significant negative influence on desire's role in the investment decision. However,
since desire still had a significant positive main effect on the investment decision, its influence seems considerable, regardless of the funding status. To answer the research question, the funding status had a significant impact on the amount invested. People who learned that the crowdfunding project was close to reaching its goal invested more than before, while those who learned that the funding goal was unlikely to be reached invested less.

5.3. Contribution and Implications

The role of emotions in investment scenarios has grown in importance in this century, as it was long believed that people's rational decisions are only impacted by cognitive and situational constraints (Lerner et al. 2015). This thesis reinforced existing beliefs that emotions influence investment decisions (Aliya and Bansal 2018; Shiv et al. 2005; Seo and Barrett 2007). It also contributed new findings, such as the positive impact of desire on investment decisions, which has not been previously analysed. Moreover, this research uncovered new knowledge about the negative effect of anger in crowdfunding scenarios, a topic only previously explored in the broader context of investment situations (Gambetti and Giusberti 2012; Bernaola, Willows, and West 2021). While financial literacy didn't strongly moderate the impact of emotions, this study confirmed that financially literate individuals are less influenced by behavioural biases (Takeda et al. 2013) and more confident about investing larger amounts, especially in situations of high uncertainty regarding the achievement of the funding goal. Furthermore, the thesis contributed to a better understanding of the influence of funding status. A high funding status encouraged participants to invest more, affirming the herding bias (Astebro et al. 2018), whereas a low funding status led to the opposite effect, validating Zaggl and Block (2019).

The practical implications of this study are most relevant to start-ups or anyone planning to launch a crowdfunding campaign in the future. The goal with project pitches should be to evoke positive emotions in potential backers, as the study found that positive emotions led to more investments, while negative emotions significantly reduced investments. Further, crowdfunding projects should aggressively recruit backers, particularly early in the campaign, as many potential investors are influenced by the funding status and the investment decisions of others. While other factors also impact the success of a crowdfunding campaign, such as how potential investors evaluate the project's potential, focusing on presenting a pitch video that elicits positive emotions and promoting the project heavily, especially shortly after its launch, can make successful funding more likely.
5.4. Limitations and Future Research

With this master's thesis, I was able to confirm several insights mentioned earlier. However, these implications only describe the behaviour observed within my sample. Due to the sampling technique employed, it's not feasible to generalize these results to a broader population (Acharya et al. 2013). Furthermore, the method of emotion measurement might have influenced the findings. On one hand, people often self-report emotions in a way that differs from their genuine feelings. On the other hand, the measurement of valence and arousal with TAWNY is likely not 100 per cent accurate. The precise measurement of financial literacy also poses challenges, as researchers disagree on which questionnaire accurately captures it. While the questionnaire used in the experiment has been validated by multiple scholars, it's not universally agreed upon. Therefore, it's possible that key independent variables may have been inaccurately represented, which could have skewed the results. Lastly, there are likely other factors that influence investment decisions in crowdfunding that were not considered in this study. Due to the scope of this thesis, it was necessary to limit the factors considered.

Looking forward, there are several paths for future research to expand our understanding of emotions' impact on investment decisions. Replicating this study with a random sampling strategy would yield generalizable results if the outcomes can be reproduced. Another interesting avenue for exploration could be the role of idea evaluation in emotional influence on investment decisions. In all models, idea evaluation significantly affected the investment decision, suggesting that further examination of the link between idea evaluation and emotions might reveal new patterns. Also, conducting the study with a different stimulus could result in more robust findings, provided the outcomes align with the current ones. A universally agreed-upon framework for defining arousal and financial literacy would enable better comparisons across studies and hence a deeper understanding of these concepts. To further comprehend the role of emotions in crowdfunding, future studies could analyze different emotions or focus on other aspects of a crowdfunding project, such as founder characteristics and the information material provided.
6. Conclusion

This study determined a statistically significant effect of both anger and desire on investment decisions. The negative influence of anger and the positive impact of desire on the likelihood of investment occurring was a novel finding in this experimental setting. Although the moderating effect of financial literacy on investment decisions wasn't confirmed, financial literacy did directly influence both the propensity to invest and the amount invested, resulting in increased investment activities. However, the study didn't find a significant influence of core affect on investment decisions. This doesn't exclude the possibility of affect playing a role, as different methods of measuring affect might yield different results. Moreover, the study showed that the funding status significantly influenced the amount invested, suggesting that participants' decisions were swayed by the majority's choice. Higher funding status led to increased investments, while lower funding status led to decreased investments. Nevertheless, it's crucial to note that these findings only represent the behaviour within the sample of this study, and making broad generalizations would be premature. As research on emotions in investment decisions, including crowdfunding, is still an emerging field with ongoing debates, this study contributes to the body of knowledge by identifying certain patterns within a small sample size. Future research could extend and replicate this study to achieve greater generalizability and validity of the results, enhancing our understanding of the role of emotions and other factors in investment decisions.
References


Wang, Yan, Wei Song, Wei Tao, Antonio Liotta, Dawei Yang, Xinlei Li, Shuyong Gao, et al. 2022. “A Systematic Review on Affective Computing: Emotion Models, Databases,


Appendix

Part A - Additional analysis:

1. Analysing the moderating effect of emotional expressivity

Before the pre-registration of the experiment, I formulated another set of hypotheses which aren’t relevant to my research question. For purposes of transparency, those hypotheses get quickly analysed here.

Emotionally expressive individuals tend to outwardly display their emotions more than others, but the subjective experience of emotions remains the same regardless of whether someone is emotionally expressive or not (J. J. Gross and Levenson 1993). However, we currently lack knowledge about the impact of emotional expressivity on the moderation of emotions in investment decision-making. In order to gain a better understanding of how emotional expressivity influences desire, anger and core affect in investment decisions, I have formulated the following hypotheses:

**H4a: Emotional expressivity moderates the relationship between desire and investment decisions. The higher the level of emotional expressivity the stronger the correlation between desire and investment decisions.**

**H4b: Emotional expressivity moderates the relationship between anger and investment decisions. The higher the level of emotional expressivity the stronger the correlation between anger and investment decisions.**

**H4c: Emotional expressivity moderates the relationship between the core affect and investment decisions. The higher the level of emotional expressivity the stronger the correlation between core affect and investment decisions.**

The analysis was conducted the same way as for the set of hypotheses analysing the moderating effect of financial literacy. The only difference was the exchange of financial literacy for emotional expressivity. None of the three hypotheses could be accepted as no statistically significant results were found. The following three tables present the results of the logistic regressions.
### H4a

<table>
<thead>
<tr>
<th>Predictors</th>
<th>Odds Ratios</th>
<th>CI</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>0.01</td>
<td>0.00 – 1.32</td>
<td>0.072</td>
</tr>
<tr>
<td>desire</td>
<td>1.08</td>
<td>0.39 – 3.04</td>
<td>0.884</td>
</tr>
<tr>
<td>EE</td>
<td>0.73</td>
<td>0.32 – 1.61</td>
<td>0.444</td>
</tr>
<tr>
<td>risk</td>
<td>0.99</td>
<td>0.80 – 1.22</td>
<td>0.915</td>
</tr>
<tr>
<td>IE overall</td>
<td>3.96</td>
<td>1.61 – 11.04</td>
<td><strong>0.005</strong></td>
</tr>
<tr>
<td>desire * EE</td>
<td>1.12</td>
<td>0.89 – 1.42</td>
<td>0.349</td>
</tr>
</tbody>
</table>

Observations: 121  
$R^2$ Tjur: 0.254

### H4b

<table>
<thead>
<tr>
<th>Predictors</th>
<th>Odds Ratios</th>
<th>CI</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>0.00</td>
<td>0.00 – 0.11</td>
<td><strong>0.007</strong></td>
</tr>
<tr>
<td>anger</td>
<td>1.24</td>
<td>0.03 – 80.54</td>
<td>0.909</td>
</tr>
<tr>
<td>EE</td>
<td>1.62</td>
<td>0.57 – 6.05</td>
<td>0.415</td>
</tr>
<tr>
<td>risk</td>
<td>1.13</td>
<td>0.93 – 1.39</td>
<td>0.232</td>
</tr>
<tr>
<td>IE overall</td>
<td>7.91</td>
<td>3.12 – 23.94</td>
<td><strong>&lt;0.001</strong></td>
</tr>
<tr>
<td>anger * EE</td>
<td>0.65</td>
<td>0.20 – 1.56</td>
<td>0.400</td>
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Observations: 121  
$R^2$ Tjur: 0.264
### Investment_Decision

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<th>p</th>
</tr>
</thead>
<tbody>
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<td>(Intercept)</td>
<td>0.00</td>
<td>0.00 – 0.06</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>affect</td>
<td>0.59</td>
<td>0.01 – 32.12</td>
<td>0.800</td>
</tr>
<tr>
<td>EE</td>
<td>1.06</td>
<td>0.76 – 1.49</td>
<td>0.734</td>
</tr>
<tr>
<td>risk</td>
<td>1.09</td>
<td>0.90 – 1.32</td>
<td>0.388</td>
</tr>
<tr>
<td>IE overall</td>
<td>5.55</td>
<td>2.40 – 14.79</td>
<td>&lt;0.001</td>
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<tr>
<td>affect * EE</td>
<td>1.26</td>
<td>0.62 – 3.05</td>
<td>0.568</td>
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Observations 121  
R² Tjur 0.193

2. Full tables of financial literacy’s main effect

No Funding Status

### Investment_Decision

<table>
<thead>
<tr>
<th>Predictors</th>
<th>Odds Ratios</th>
<th>CI</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>0.00</td>
<td>0.00 – 0.02</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>FL total</td>
<td>1.16</td>
<td>0.97 – 1.39</td>
<td>0.101</td>
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<tr>
<td>risk</td>
<td>1.04</td>
<td>0.86 – 1.26</td>
<td>0.700</td>
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<tr>
<td>IE overall</td>
<td>6.69</td>
<td>2.88 – 17.85</td>
<td>&lt;0.001</td>
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Observations 121  
R² Tjur 0.197
No Funding Status

<table>
<thead>
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<th>Predictors</th>
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<th>CI</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>-2.16</td>
<td>-3.81 – -0.51</td>
<td><strong>0.010</strong></td>
</tr>
<tr>
<td>FL total</td>
<td>0.11</td>
<td>0.02 – 0.20</td>
<td><strong>0.017</strong></td>
</tr>
<tr>
<td>risk</td>
<td>0.07</td>
<td>-0.03 – 0.17</td>
<td>0.180</td>
</tr>
<tr>
<td>IE overall</td>
<td>0.65</td>
<td>0.25 – 1.04</td>
<td><strong>0.001</strong></td>
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Observations 121
R² 0.139

Funding Status 90%

<table>
<thead>
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<th>Predictors</th>
<th>Odds Ratios</th>
<th>CI</th>
<th>p</th>
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</thead>
<tbody>
<tr>
<td>(Intercept)</td>
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<td>0.00 – 0.09</td>
<td><strong>0.008</strong></td>
</tr>
<tr>
<td>FL total</td>
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<td>risk</td>
<td>1.17</td>
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<td>0.312</td>
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<tr>
<td>IE overall</td>
<td>7.03</td>
<td>2.05 – 32.52</td>
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Observations 56
R² Tjur 0.189

Funding Status 90%

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<td>-5.10 – -0.06</td>
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<td>FL total</td>
<td>0.02</td>
<td>-0.12 – 0.16</td>
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<tr>
<td>risk</td>
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<td>0.07 – 0.37</td>
<td><strong>0.005</strong></td>
</tr>
<tr>
<td>IE overall</td>
<td>0.78</td>
<td>0.18 – 1.37</td>
<td><strong>0.010</strong></td>
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Observations 56
R² 0.198
3. Testing for multicollinearity

<table>
<thead>
<tr>
<th></th>
<th>desire</th>
<th>risk</th>
<th>IE overall</th>
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<tbody>
<tr>
<td>H1a</td>
<td>1.09</td>
<td>1.10</td>
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</tr>
<tr>
<td>H1b</td>
<td>1.08</td>
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<td>1.07</td>
</tr>
<tr>
<td>H1c</td>
<td>1.01</td>
<td>1.02</td>
<td>1.01</td>
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4. Testing the linearity of the logit:

**H1a**

<table>
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<th>p</th>
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<td>0.087</td>
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<tr>
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<td>0.286</td>
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<tr>
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<td>1.62</td>
<td>0.19 – 13.37</td>
<td>0.656</td>
</tr>
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<td>log risk</td>
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<td>0.36 – 1.91</td>
<td>0.640</td>
</tr>
<tr>
<td>IE overall</td>
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<td>0.02 – 938160999888176640.00</td>
<td>0.173</td>
</tr>
<tr>
<td>log IE overall</td>
<td>0.00</td>
<td>0.00 – 12.83</td>
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Observations: 121

$R^2$ Tjur: 0.277

**H1b**

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<th>p</th>
</tr>
</thead>
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<td>anger</td>
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<td>risk</td>
<td>2.95</td>
<td>0.39 – 23.88</td>
<td>0.298</td>
</tr>
<tr>
<td>log risk</td>
<td>0.68</td>
<td>0.30 – 1.52</td>
<td>0.352</td>
</tr>
<tr>
<td>IE overall</td>
<td>36661.43</td>
<td>0.00 – 5033385305992980.00</td>
<td>0.381</td>
</tr>
<tr>
<td>log IE overall</td>
<td>0.02</td>
<td>0.00 – 326.19</td>
<td>0.487</td>
</tr>
</tbody>
</table>

Observations: 121

$R^2$ Tjur: 0.271
Part B: Experimental Setup

How TAWNY measures emotions

Sequence of the experiment:

Dear Participant,
welcome to our experiment in which we would like to investigate the influence of emotions on investment decisions. We thank you already very much for your participation. You are making an important contribution to the success of our master's thesis.
The experiment will take about 10 minutes. We ask you to be fully focused and not distracted during the experiment.

The experiment will consist of different parts aimed to measure your emotional reaction and your investment decision. First, you will watch a video and then answer some questions. For this, please make sure that your front camera is working and not covered. For a smooth process please use the Google Chrome browser. Please answer the questions honestly and spontaneously to ensure an authentic response. For participating in our experiment you will receive a budget of 5€. In the course of the experiment you will have to decide whether to invest it or not. If you invest, you have the chance to earn a higher profit as a result. If you don't invest, you will keep the 5€ as compensation for your participation.

It is important for us to point out that all your data will be kept strictly confidential and will only be used for the purpose of this study as part of our master's thesis. Your personal information and data will not be shared with third parties or used for any purpose other than the study. By clicking on "Start Experiment" you agree to the privacy policy.

We hope you feel comfortable during the experiment and thank you again for your participation. If you have any questions, please do not hesitate to contact us.

Elias Moser: elias.moser@student.uibk.ac.at
Moritz Barmann: moritz.barmann@student.uibk.ac.at
**What is the first letter of your mother's first name? (capital letter)**

**What is the last letter of your first name? (lower case letter)**

**Please enter the day of your birth as a number between 1 and 31. (e.g. April 09, 1988 -> 9)**

Only numbers may be entered in this field.

**What is the first letter of your father's first name? (lower case letter)**

---

**Please indicate your current mood with regard to the following categories:**

Today. I am feeling… | Bad - Good
--- | ---
1 | 2 | 3 | 4 | 5
Very bad | Somewhat bad | Neutral | Somewhat good | Very good

Today. I am feeling… | Unpleasant - Pleasant
--- | ---
1 | 2 | 3 | 4 | 5
Very unpleasant | Somewhat unpleasant | Neutral | Somewhat pleasant | Very pleasant

Today. I am feeling… | Sad - Happy
--- | ---
1 | 2 | 3 | 4 | 5
Very sad | Somewhat sad | Neutral | Somewhat happy | Very happy
Investing carries risks, including loss of capital and illiquidity.

THIS™ - Crowdfunding Pitch

- What is the first letter of your mother’s first name? (capital letter)

- What is the last letter of your first name? (lower case letter)

- Please enter the day of your birth as a number between 1 and 31 (e.g. April 09, 1998 -> 9)

  Only numbers may be entered in this field.

- What is the first letter of your father’s first name? (lower case letter)
While watching the video, to what extent did you experience these emotions?

<table>
<thead>
<tr>
<th></th>
<th>Not at all</th>
<th>Slightly</th>
<th>Somewhat</th>
<th>Moderately</th>
<th>Quite a bit</th>
<th>Very much</th>
<th>An extreme amount</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wanting</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Desire</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Longing</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Anger</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rage</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mad</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pissed off</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Equity-based crowdfunding has become an increasingly popular way for privately held entrepreneurial companies to raise capital from the public. This process involves offering securities, often in the form of equity stakes, to funders through online platforms. In exchange for investing in the business, the funder receives an annual dividend and a portion of the profits in the event of an exit scenario.

Equity-based crowdfunding is an exciting opportunity for investors to invest in emerging companies and benefit from their success. This type of crowdfunding offers an alternative to traditional forms of investment. Of course, there is also a risk that the company will fail and you lose your invested capital.

**Investment Summary:**
- **Target:** 100,000 ECU
- **Type:** Equity - Series B Preferred shares
- **Valuation (pre-money):** 4,000,000 ECU
- **Equity offered:** 5.00%
- **Share price:** 50 ECU

Based on the video you just watched, would you like to invest in the product and support "THIS"?
Remember your budget of 1,000 ECU.

- Choose one of the following answers:
  - Yes, invest now!
  - No, I don’t want to invest!

The acquisition of this security is associated with considerable risks and may lead to the complete loss of the invested assets. The promised return is not guaranteed and may also be lower.

Considering your budget of 1,000 ECU, how much do you want to invest?

- Choose one of the following answers:
  - 250 ECU
  - 500 ECU
  - 750 ECU
  - 1000 ECU

In crowdfunding, the reward depends on the amount of capital invested.
Potential investors can view the current funding status of a project on crowdfunding websites to assess its popularity in the community.

You can find the current funding status of the 'THIS' presented below:

Funding Status

[Image of a funding status screen showing 90% of funding goal accomplished with 30 of 60 funding days remaining]

Attention: For this question, you will receive a new budget, thus you have again the opportunity to invest 1,000 ECU. Uninvested capital from the previous question will not be taken into account.

Given this additional information, would you like to invest in the product and support ‘THIS’?

- Choose one of the following answers

  - Yes, invest now!
  - No, I don’t want to invest!

The acquisition of this security is associated with considerable risks and may lead to the complete loss of the invested assets. The promised return is not guaranteed and may also be lower.

Considering your new budget of 1,000 ECU, how much do you want to invest?

- Choose one of the following answers

  - 250 ECU
  - 500 ECU
  - 750 ECU
  - 1000 ECU

In crowdfunding, the reward depends on the amount of capital invested.

For each statement below, please indicate your agreement or disagreement.

<table>
<thead>
<tr>
<th>1 - Strongly disagree</th>
<th>2</th>
<th>3</th>
<th>4 - Neutral</th>
<th>5</th>
<th>6</th>
<th>7 - Strongly agree</th>
</tr>
</thead>
<tbody>
<tr>
<td>I am an emotionally expressive person.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>What I’m feeling is written all over my face.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I experience my emotions very strongly.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>My body reacts very strongly to emotional situations.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

How would you rate the idea in terms of...

<table>
<thead>
<tr>
<th>1 - Very low</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5 - Very high</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall potential</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market potential</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Novelty/Creativity</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Practical feasibility</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Risk</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
To test your financial knowledge, we invite you to answer a couple of questions. The quiz consists of a series of questions that vary in difficulty, and your task is to answer each question to the best of your ability.

We encourage you to approach each question thoughtfully and do your best but also keep in mind that your performance on this quiz will not have any impact on the payout of the experiment.

Remember not to get too caught up on any one question and stay focused throughout the quiz. We wish you the best of luck and appreciate your participation in our experiment.

Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year you would be able to buy:

- More than today with the money in this account
- Exactly the same as today with the money in this account
- Less than today with the money in this account

Do you think that the following statement is true or false? Bonds are normally riskier than stocks.

- True
- False
- Don’t know
- Refuse to answer

Considering a long time period (for example 10 or 20 years), which asset described below normally gives the highest return?

- Savings account
- Stocks
- Bonds
- Don’t know
- Refuse to answer

Normally, which asset described below displays the highest fluctuations over time?

- Savings account
- Stocks
- Bonds
- Don’t know
- Refuse to answer

When an investor spreads his money among different assets, does the risk of losing a lot of money:

- Increase
- Decrease
- Stays the same
- Don’t know
- Refuse to answer
Do you think that the following statement is true or false? If you were to invest \$1,000 in a stock mutual fund, it would be possible to have less than \$1,000 when you withdraw your money.

☐ True
☐ False
☐ Don't know
☐ Refuse to answer

Do you think that the following statement is true or false? A stock mutual fund combines the money of many investors to buy a variety of stocks.

☐ True
☐ False
☐ Don't know
☐ Refuse to answer

Do you think that the following statement is true or false? A 15-year mortgage typically requires higher monthly payments than a 30-year mortgage, but the total interest paid over the life of the loan will be less (both with the same loan amount).

☐ True
☐ False
☐ Don't know
☐ Refuse to answer

Suppose you had \$100 in a savings account and the interest rate is 5% per year and you never withdraw money or interest payments. After 5 years, how much would you have on this account in total?

☐ More than \$200
☐ Exactly \$200
☐ Less than \$200
☐ Don't know
☐ Refuse to answer

Which of the following statements is correct?

☐ Once one invests in a mutual fund, one cannot withdraw the money within five years.
☐ Mutual funds can invest in several assets, for example invest in both stocks and bonds.
☐ Mutual funds pay a guaranteed rate of return which depends on the past performance of competitors.
☐ None of the above
☐ Don't know
☐ Refuse to answer
Which of the following statements is correct? If somebody buys a bond of firm B:

- The person owns a part of firm B
- The person has lent money to firm B
- The person is liable for firm B's debts
- None of the above
- Don't know
- Refuse to answer

Suppose you owe 3,000€ on your credit card. You pay a minimum payment of 30€ each month. At an annual percentage rate of 12% (or 1% per month), how many years would it take to eliminate your credit card debt if you made no additional new debt?

- Less than 5 years
- Between 5 and 10 years
- Between 10 and 15 years
- Never
- Don't know
- Refuse to answer

Have you invested in financial products like bonds, stocks, ETFs, etc. at least once?

- Yes
- No
- Refuse to answer

Please assess yourself:

<table>
<thead>
<tr>
<th>1 - Not at all risk-tolerant</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10 - Highly risk-tolerant</th>
</tr>
</thead>
<tbody>
<tr>
<td>Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Yes</td>
</tr>
<tr>
<td>Are you a person who is fully prepared to take risks in investment decisions or do you try to avoid taking risks?</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Yes</td>
</tr>
</tbody>
</table>

What are your eating habits?

<table>
<thead>
<tr>
<th></th>
<th>No</th>
<th>Yes</th>
</tr>
</thead>
<tbody>
<tr>
<td>I like to eat meat substitutes.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>I eat mainly meat heavy.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>I eat mainly vegetarian.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>I eat mainly vegan.</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Declaration of Academic Honesty
I hereby declare in lieu of oath by my own signature that I have written this thesis independently and
have not used any sources or aids other than those indicated. All passages that have been taken
verbatim or in terms of content from the stated sources are identified as such.

The present work has not yet been submitted in the same or similar form as a

09.06.2023
Date

09.06.2023
Signature