ECO5066W

Masters Dissertation

Risk Attitudes and Affective States among Young Adults

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Abstract

This study examines how negative emotions influence risk attitudes and chance attitudes profiles among young adults using data from a novel behaviour modification programme targeted at young adults in South Africa. Risk attitudes are estimated structurally by assuming a standard power utility function for the risky prospects they face in the risk elicitation experiment. The power parameter is recovered, and checks are performed for evidence of risk aversion and probability distortions.

We find that while both the control and treatment groups exhibit risk aversion, the programme does not significantly alter risk aversion overall. However, significant treatment effects emerge with respect to probability distortion, suggesting that the programme fosters behaviour more closely aligned with expected utility maximisation. The programme appears to decrease the likelihood that individuals never experience anger or hostility. However, the effects on anger and hostility do not account for the observed treatment effects on probability distortions. Furthermore, individuals who never experience nervousness tend towards risk neutrality, while those who experience it are typically risk averse. Interestingly, both nervousness and fear correlate negatively with probability distortions, indicating a more pessimistic approach to risk among those who do not experience these emotions. This pattern holds across both the treatment and control groups, suggesting that these emotions remain relatively stable in the programme context.

These findings emphasise the importance of considering affective states in designing interventions to address risky behaviours among young adults, contributing to improved public health outcomes.

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1 Introduction

Individual decisions are influenced by perceptions of risks and opportunities, and emotions play a critical role in shaping how these decisions are made. For trivial decisions, such as whether to snooze an alarm, the emotional stakes are low. However, in more consequential decisions, such as smoking or unprotected sex, emotions such as anxiety, fear, or excitement strongly influence behaviour (Caffray & Schneider 2000). Chemical imbalances in the brain, which can result in behaviours such as excessive enthusiasm or a focus on immediate rewards, contribute to risky economic decisions. For example, fear of failure can cause people to underestimate their chances of success in entrepreneurial ventures.

Recent statistics reveal concerning trends in risky behaviours among South African youth, highlighting growing public health challenges. Approximately 30% of adolescents report having unprotected sex, contributing to the high rates of HIV/AIDS in the country, particularly among young women. Furthermore, the prevalence of alcohol use among young people remains high, with about 40% of high school students reporting binge drinking in the past month (Reddy, Zuma et al. 2021). Substance abuse is also on the rise, with the 2022 South African Community Epidemiology Network on Drug Use report indicating a significant increase in methamphetamine use, particularly among younger populations (Duncan, Bhana et al. 2022). These high rates of substance abuse, unprotected sexual practices, and involvement in violent crimes highlight the need to understand the factors influencing individual attitudes toward risk. Such risky behaviours suggest an underlying role for emotional states, such as peer pressure-induced excitement or fear of exclusion, in shaping young people's attitudes toward risk.

Youth unemployment, which hovers around 55% in 2023, contributes to economic instability and social challenges (Statistics South Africa 2023). Individual attitudes toward risk significantly influence entrepreneurial intentions and behaviours, with research showing that a positive attitude toward risk improves the likelihood of participating in entrepreneurial activities (Shapero & Sokol 1982).

Affect refers to the broad domain of subjective feelings and emotional experiences that strongly shape decision making, particularly in uncertain or high-risk contexts. It is widely believed that affective states play a powerful role in modifying attitudes toward risk. For example, depression is associated with disordered eating (Smith 2009), anger with reckless behaviour (Ahn 2010), and anxiety with reduced risk taking (Lerner & Keltner 2001).

The concept of *risk taking* generally includes behaviours that pose a danger or harm to people and their surroundings (Hawley 2011). To effectively address risk taking, it is essential to understand how individuals make decisions under uncertainty, a topic widely explored in subfields of economics, such as behavioural economics and decision theory (Loewenstein 2000). The hypothesis of *Risk-as-Feelings*, proposed by Loewenstein (2000), posits that emotions and feelings significantly shape an individual's perception and response to risk. This framework suggests that affective states not only influence the likelihood of engaging in risky behaviour but also affect how individuals evaluate potential outcomes, highlighting the importance of considering emotional dimensions in risk-related decision making.

Traditional approaches, such as expected utility theory (EUT), assume that individuals assess the desirability and likelihood of potential outcomes and integrate this information to make decisions (Karni, Maccheroni & Marinacci 2015). However, empirical evidence suggests that people do not always make decisions using calculated reasoning, especially in conditions of uncertainty or emotional stress (Starmer 2000). Emotional interference complicates rational decision making, particularly when individuals struggle to foresee the future consequences of their current choices (Loewenstein, Weber, Hsee & Welch 2001).

In the context of risky behaviour, emotions such as fear, nervousness, and anger distort risk perceptions, influencing decisions that deviate from rational models such as expected utility theory. Smoking, for example, is often associated with time discounting, where people place less value on future outcomes.

This misalignment between emotional impulses and rational decision-making highlights the importance of accounting for emotions in any intervention aimed at reducing risky behaviours.

This study focusses on how the *Activate! Change Drivers* programme affects risk attitudes and probability distortion among young adults, compared to a control group randomised out of the programme. The programme consists of interventions designed to promote both private interests (e.g., entrepreneurial innovation) and the public good (e.g., civic engagement). Its interventions foster the development of prosocial preferences, such as altruism and trust, while also targeting mindset shifts that reduce destructive risk-taking behaviour, civic apathy, and impatience.

The programme emphasises emotional resilience and social cohesion, designed to regulate the emotional responses of participants to uncertainty, which has been shown to influence risk attitudes. By improving emotional regulation through workshops and fostering goal-orientated behaviour, the programme is likely to reduce negative emotions such as fear and nervousness, which are associated with increased risk aversion and distorted probability weighting (Loewenstein et al. 2001). Thus, the intervention could theoretically shift participants' decision-making toward more rational and utility-maximising behaviour.

2 Hypotheses

- **Hypothesis 1**: Participation in the programme will reduce probability distortions, leading to more linear probability weighting among participants, indicative of less emotional interference in decision making.

- **Hypothesis 2**: The programme will reduce risk aversion by improving emotional regulation. Participants are expected to show lower levels of fear and nervousness, which are associated with higher tolerance to risk.

- **Hypothesis 3**: Negative emotions such as fear, anxiety, and nervousness will correlate with greater probability distortion and increased risk aversion. Participants with reduced levels of these emotions are expected to exhibit more rational decision making, with lower risk aversion and less distorted probability weighting.

The risk attitudes of this sample are structurally estimated by assuming a standard power utility function for the risky prospects they face in the risk elicitation experiment. We recover the power parameter r and check for evidence of risk aversion. We then examine whether participants distort probabilities. Three key ways in which probabilities can be distorted include editing stated probabilities, eliminating extreme probabilities (e.g., prospects that occur with certainty), up-weighting small probabilities, and down-weighting large probabilities. Drawing on evidence from cognitive sciences, these psychological tendencies are estimated using inverse S-shaped probability weighting functions.

We find that both the control and treatment groups are risk averse and that the programme does not significantly change risk aversion (r). However, strong treatment effects on probability distortion (γ) are observed. Programme participants exhibit more linear probability weighting functions, while nonparticipants display an inverted S-shaped curve, consistent with greater emotional interference in risk perception. In other words, the programme induces behaviour resembling expected utility maximisation, implying that psychological dispositions accounting for probability distortions are reduced by the end of the programme.

In investigating the impact of the programme on negative emotions, we find that it tends to decrease the likelihood that participants report never feeling anger or hostility. However, the effects of the interaction on anger and hostility are not significant, suggesting that these emotions do not explain the effects of the programme on probability distortions. Individuals who never experience nervousness tend to display risk neutrality, while those who feel nervous are risk-averse.

Contrary to our hypothesis, both nervousness and fear are negatively related to probability distortions. Participants who do not experience fear or nervousness display a more pessimistic approach to risk, exhibiting a more pronounced S-shaped probability weighting function, indicating a higher sensitivity to small probabilities and potential losses. This result holds for both the treatment and control groups, suggesting that nervousness and fear may be relatively immutable emotions in the context of this programme.

The structure of this paper unfolds systematically. We begin with an exploration of the neurological foundations of emotional judgments, followed by a theoretical framework underpinning the study, the *Risk-as-Feelings* hypothesis. Next, we provide a comprehensive overview of the data used, outline the methodology applied, and finally present the key findings. This study offers important information on how structured interventions like *Activate!* can influence perceptions of risk, decision making, and emotional regulation.

3 Neurobiological Foundations of Emotional Judgements

3.1 Key Elements of Emotion

Emotions are not just transient feelings, but complex processes that influence decision making, particularly in risky contexts. These processes involve subjective experience, expressive behaviour, and physiological reactions (Hamann & Canli 2004). The subjective experience of emotion is shaped by factors such as personality, affective disposition, and biological variables, including sex and genotype. These individual differences affect neural activity, particularly in regions of the brain responsible for processing emotions, such as the prefrontal cortex and the limbic system (Eugene, Lévesque, Mensour et al. 2003).

From a neurobiological perspective, emotions trigger peripheral physiological responses controlled by the autonomic nervous system, leading to involuntary reactions, such as ducking when faced with perceived danger. In contrast, expressive behaviours such as smiling or frowning are voluntary actions shaped by cultural norms and personal experiences.

In this study, we explore how emotions shape risk attitudes, particularly in the context of behavioural interventions. Understanding these neurobiological foundations is helpful in examining how programmes like *Activate!* may alter emotional states and consequently risk preferences.

3.2 The Affect Heuristic

The *affect heuristic* describes how individuals rely on emotional reactions as shortcuts in decision-making, often simplifying complex choices (Slovic, Finucane, Peters & MacGregor 2007). *Affect*, which encompasses emotions and moods, significantly shapes perceptions of risk and reward (Barrett & Salovey 2002, Lerner, Li, Valdesolo & Kassam 2015). For example, fear can magnify perceived risks, while positive emotions, such as happiness, can encourage more risk-taking behaviour.

This study builds on the hypothesis that interventions targeting emotional states can modify risk preferences. Emotional intensity is central to this process; As emotional intensity increases, individuals are more likely to rely on affective responses rather than rational analysis (Loewenstein et al. 2001). This heuristic directly informs the broader investigation of how emotional shifts, triggered by structured interventions, influence decision making under uncertainty.

3.3 Dual Thinking Systems

Aligned with the *risk as feelings* hypothesis discussed earlier, the dual system theory of decision making highlights the two cognitive processes of the brain: System 1 (intuitive, emotional) and System 2 (deliberative, logical) (Kahneman 2003). System 1 operates quickly and emotionally, while System 2 functions more slowly, relying on deliberate reasoning. It is essential to recognise that biases introduced by System 1 are not inherently negative. In a study by Bechara and colleagues, participants with vmPFC damage (patients) and those without vmPFC damage (non-vmPFC patients) engaged in a gambling task aimed at maximising earnings. The task involved four decks of cards, two with high amounts ($100) and two with lower amounts ($50). Participants, without prior knowledge of the number of cards they could select, were free to switch between decks. Although high-winning decks occasionally suffered substantial losses, influencing the decision to switch, both groups initially avoided the high-paying deck after encountering significant losses. In particular, vmPFC patients returned to high-paying decks more quickly after a loss compared to non-vmPFC patients, despite expressing a strong desire to gain (Loewenstein et al. 2001, pp. 270). Brain imaging studies during the task revealed that somatic markers of non-vmPFC patients developed early in the trials, providing signals that guide subsequent card choices. In contrast, vmPFC patients were unable to generate these signals, lacking emotional memory to learn from their mistakes. The vmPFC region of the brain plays a crucial role in decision-making under uncertainty (Manes, Sahakian, Clark, Rogers, Antoun, Aitken & Robbins 2002, Rogers, Everitt, Baldacchino, Blackshaw, Swainson, Wynne, Baker, Hunter, Carthy, Booker et al. 1999, Sanfey, Rilling, Aronson, Nystrom & Cohen 2003).

Our hypothesis suggests that interventions like *Activate!* may help participants shift from emotion-driven decision-making (System 1) to more deliberate and logical choices (System 2), thus reducing risky behaviours. This dynamic sheds light on how emotional and cognitive processes work together to shape risk-related decisions.

3.4 The Role of the Ventromedial Prefrontal Cortex (vmPFC)

The ventromedial prefrontal cortex (vmPFC) plays an essential role in integrating emotional responses with cognitive decision making, particularly under conditions of uncertainty and risk. The vmPFC processes emotional signals, or *somatic markers*, which help guide decisions when logical reasoning alone is insufficient (Bechara, Tranel, Damasio, Adolphs, Rockland & Damasio 1995, Damasio 1994). Furthermore, the amygdala, which interacts with the vmPFC, is key to processing emotional stimuli and influencing subsequent decisions (Phelps 2006). Programmes like *Activate!* aim to modify both emotional states and risk attitudes. If such interventions impact emotional processing within the vmPFC-amygdala network, they can effectively alter participants' risk perceptions and behaviours.

4 Conceptual Framework: Risk-as-Feelings

During the past two decades, there has been a growing body of research that examines the influence of emotions on economic decision making, with numerous studies highlighting their impact (Mellers 2000, Kahneman 2003). Building on the previously introduced *Risk-as-Feelings* hypothesis (Loewenstein 2000), which posits that emotions can lead to risk assessments that deviate from rational cognitive evaluations, several studies have provided empirical support for this idea. Early research on risk perception demonstrated how affective responses often influence risk behaviour (Fischhoff, Lichtenstein, Derby, Slovic & Keeney 1984, Slovic, Fischhoff & Lichtenstein 1980). According to Loewenstein, the interplay between affect and cognition is a critical factor in the formation of risk-related decisions, as illustrated in Figure 4.

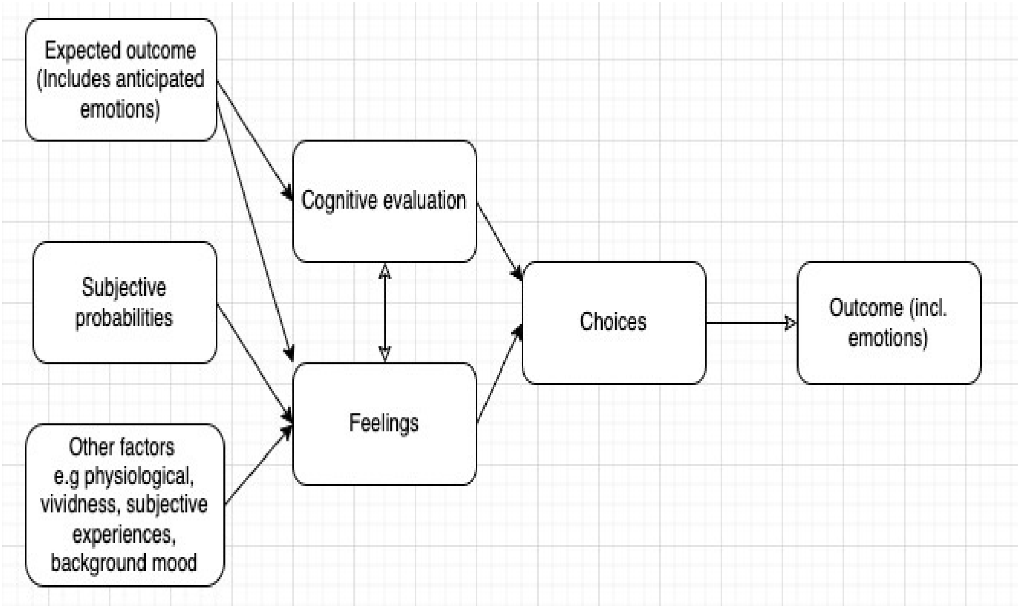

Figure 1: The risk-as-feelings model taken from Loewenstein (2000)

The *Risk-as-Feelings* hypothesis identifies two key roles for emotions in decision making. *Anticipated* emotions, which refer to beliefs about future feelings, are integrated into the expected utility model (EU), where individuals predict emotional consequences to choose actions that maximise positive emotions (Lerner & Keltner 2001, pp. 620). In contrast, *immediate* emotions directly affect decisions without cognitive control, such as panic responses to threatening stimuli or altering expectations of future outcomes. For example, a young adult may anticipate the fear of addiction and avoid experimenting with narcotics. However, peer pressure and immediate appeal of the offer can override this fear, leading to riskier decisions. Whether anticipated or immediate emotions dominate is an empirical question.

The distinction between these two types of emotions is important because they often influence behaviour in different ways. Immediate emotions can cause people to react impulsively, while anticipated emotions shape decisions based on future consequences. This framework offers critical insights into how interventions like the *Activate!* programme could influence decision making by addressing both the cognitive and emotional components of risk.

4.1 Determinants of Emotional Responses

The *Risk-as-Feelings* hypothesis posits that emotional responses are more predictable than purely cognitive evaluations due to their distinct determinants. These determinants, described in the literature, include factors such as vividness, insensitivity to probability variations, time delay, public panic, and evolutionary preparedness (Loewenstein 2000). Here, we focus on the two determinants most applicable to our study, namely, vividness and insensitivity to probability variations.

Vividness The role of vividness in decision making and its connection to emotions and formulation is highlighted in the literature. Vividness refers to the ease with which an event or potential consequence can be envisioned or visualised. The impact of the content, context, and accessibility of decision-making information can influence risk preferences and choices (Guyse, Keller & Eppel 2002). When information is presented in a way that is easy to imagine or visualise, such as with emotive descriptions, pictures, or videos, it is more vivid, and people are more likely to have strong emotional reactions to it (Slovic et al. 2007). This emotional reaction affects the decision-making process, as illustrated in Figure 4. For example, positive or negative descriptions used to induce affect have a significant impact on the decisions taken in gambling tasks (Hinson, Whitney, Holben & Wirick 2006). Furthermore, when information is presented in a way that is difficult to imagine or visualise, such as statistical or abstract descriptions, it is less vivid and people are less likely to have strong emotional reactions to it (Hsee & Rottenstreich 2004). Framing can also affect vividness by influencing the perceived probability of an event and its potential consequences (Tversky & Kahneman 1985).

In addition, the framing effects can significantly impact decision-making, particularly in situations where emotions play a strong role. For example, if a risk is framed in terms of potential losses, people may feel more anxious and have a stronger sense of vividness about the event, as they can imagine the potential negative outcome more easily. In contrast, if risk is framed in terms of potential gains, people may feel less anxious and have a weaker sense of vividness about the event, as they have a harder time imagining the potential negative outcome (Loewenstein et al. 2001). Therefore, the degree of vividness of an event or potential consequence is critical in decision-making processes, as it creates an emotional reaction that affects cognitive evaluation and, ultimately, influences the decision-making process. The framing of information also plays a crucial role in determining how vivid an event is and can significantly impact the perceived probability of an event and its potential consequences.

Insensitivity to Probability Variations Insensitivity to probability variation is a well-documented cognitive bias in decision-making, in which people tend to overlook the probability of an event when assessing its potential impact. This results in a similar perception of risk or concern about an event, irrespective of its actual probability of occurrence. Cognitive biases such as framing, availability heuristic, and affect heuristic partly contribute to this insensitivity to probability variations, affecting how people perceive and evaluate the potential consequences of an event, and creating an emotional association with the mental images associated with the outcome of the decision. The emotions they evoke are insensitive to probability variation because these mental images are discrete. The role of emotions in decision making and their impact on insensitivity to probability variation has been widely discussed in the literature, as seen in Loewenstein's work (Loewenstein 2000, pp. 276).

To illustrate insensitivity to probability variations, Denes and colleagues conducted a study with jelly beans (Denes-Raj & Epstein 1994). In this experiment, participants were presented two bowls of jelly beans and offered the opportunity to win $1 in each 'win' trial in which they draw a red jelly bean. The two options were to draw from either a larger bowl with a lower probability of containing a red bean or a smaller bowl with a higher probability of a red bean. Surprisingly, the participants were more inclined to choose the larger bowl, although it had a lower overall probability of winning. This decision was driven by the participants' perception that the larger bowl increased their chances of winning, emphasising how individuals may neglect objective probabilities and rely on subjective mental images when assessing the likelihood of an event. Similarly,Loewenstein (2000) observed that lottery winners have the same beliefs and feelings regardless of the odds of winning, suggesting that people often neglect the probability that an outcome occurs and instead focus on subjective mental images (Loewenstein 2000). This neglect of probability in favour of subjective mental images is attributed to cognitive biases in weighing probable events, with additional influences from presentation formats (Visschers, Meertens, Passchier & De Vries 2009) and emotional states (Fehr-Duda & Epper 2012).

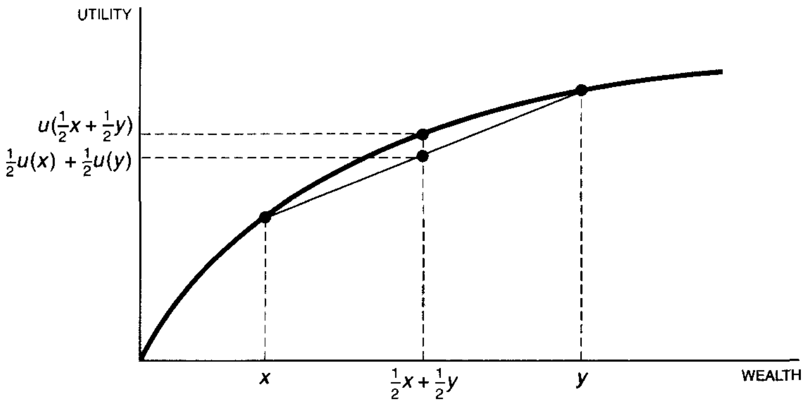

Figure 2: Expected Utility Function for Risk Aversion

The expected utility of the gamble is $0.5U(x) + 0.5U(y)$. The utility of the expected value of the gamble is $U(0.5x + 0.5y)$. The graph shows the case of risk aversion where $U(0.5x + 0.5y) > 0.5U(x) + 0.5U(y)$. *Source*: Silberberg and Suen (2000).

5 Probability Distortion and Risk Attitudes

5.1 Probability Distortion

Risk aversion manifests itself when uncertain prospects are less favoured than the expected value of those prospects. This condition holds when the utility function is concave, as depicted in the accompanying Figure 4. It should be noted that the utility of the expected value of a gamble, indicated as $U(0.5x+0.5y)$ for $y < x$, exceeds that of the expected utility of the gamble expressed as $0.5U(x)+0.5U(y)$. Within the framework of expected utility theory, risk aversion is exclusively attributed to sensitivity to outcomes, where the inverse relationship $U(0.5x+0.5y) < 0.5U(x)+0.5U(y)$ indicates a predisposition toward risk or 'risk lovingness', with strict equality implying risk neutrality. However, there is no inherent reason for risk aversion to arise solely, or even at all, due to the sensitivity of outcomes. Sensitivity to probabilities is equally, if not more, crucial in determining risk attitudes, as Peter Wakker aptly notes.

> I expect that most individuals, when they first learned about the characterisation of risk aversion through concave utility, were amazed. Utility seems to describe sensitivity to money, and this seems to be a concept different than attitude to risk. How can your feelings about money determine your risk attitude? What about your utility and behaviour for other quantitative outcomes, such as amounts of wine, life duration, or hours of listening to music? And what about your behaviour for non-quantitative outcomes such as health states? Shouldn't risk attitude have something to do with feelings about probabilities? Utility curvature does not seem to capture risk attitude in a homeomorphic manner. (Wakker 2010, pp. 147)

In fact, a long tradition in psychology, culminating in original prospect theory (Tversky & Kahneman 1974), has approached the problem of risk aversion from the point of view of probabilistic sensitivity, thus extending the expected utility framework to accommodate such psychological phenomena as editing probabilities, by up-weighting low probability events and down-weighting high probability events. The deviation from linearity in the evaluation of risky prospects, according to this tradition in psychology, has much to do with the non-linear evaluation (i.e. perception) of the probabilities associated with risky prospects (Wakker 2010).

In contrast to expected utility theory, the probability weighting function of prospect theory explains how individuals assess the consequences of decisions, considering probabilities differently than expected utility theory. Reflecting on the jelly bean experiment by (Denes-Raj & Epstein 1994), expected utility theory assumes linear weighting, suggesting that participants would maximise expected utility. However, empirical evidence shows that participants often choose options with lower expected utility.

Probability weighting allows for the distortion of probabilities, where changes in probability are perceived differently depending on their position on the probability scale. Wu and Gonzales (1996) provide an astute analogy to depict the concept; when men face a 2% probability of contracting a specific disease compared to women's 1% chance, the perceived risk for men is perceived as twice that of women. However, this identical 1% difference seems less significant when the probability of contracting the disease is closer to the midpoint of the probability scale. For example, when men have a 33% chance and women have a 32% chance of contracting the disease, the discrepancy may be seen as a negligible difference in risk between the sexes (Wu & Gonzalez 1996).

A straightforward method to address this form of probability dependency involves modelling it directly through a probability weighting function. Empirical findings support the use of this function, which typically displays an inverse S-shaped shape (Fehr-Duda & Epper 2012, pp. 570). This function captures the observation that alterations in probability are perceived more markedly near the extremes (0% and 100%) compared to the midpoint of the scale. Originating from prospect theory, formulated by Kahneman and Tversky, the probability weighting function exhibits concavity for low probabilities (indicating risk-seeking behaviour) and convexity for high probabilities (reflecting risk-averse tendencies) (Wu & Gonzalez 1996, Etchart-Vincent 2009, Abdellaoui, l'Haridon & Zank 2010).

Wu and Gonzalez's exploration of discriminability and attractiveness in the probability weighting function sheds light on the psychological mechanisms underlying risk perception and decision-making. Discriminability, which pertains to individuals' capacity to differentiate between probabilities, and attractiveness, which denotes the overall appeal of potential outcomes, are crucial factors influencing how probabilities are weighed in decision-making contexts (Wu & Gonzalez 1996).

Probability weighting functions provide a nuanced perspective on risk behaviour by separating the effects of curvature and elevation (see Figure 4 for a graphical interpretation) (Fehr-Duda & Epper 2012). Curvature captures individuals' sensitivity to changes in probabilities, with a concave curvature indicating risk aversion and a convex curvature suggesting risk-seeking behaviour (Abdellaoui et al. 2010). Moreover, the principle of diminishing sensitivity, as proposed by Tversky and Kahneman, elucidates how individuals become less responsive to changes in probability as they move away from reference points. Under the principle of diminishing sensitivity, increments near the endpoints of the probability scale are larger than increments near the middle of the scale (Wu & Gonzalez 1996). The diminishing sensitivity also applies in the domain of outcomes, the status quo usually serving as a single reference point (Wu & Gonzalez 1996). However, elevation reflects the general attractiveness of potential outcomes, influencing individual risk attitudes (Abdellaoui et al. 2010). Elevation, meanwhile, denotes the reference point from which gains and losses are evaluated (i.e., departure from linear weighing (Fehr-Duda & Epper 2012)). It represents the baseline outcome or status quo against which other outcomes are compared. In other words, elevation expresses the degree of optimism; the more elevated the curve, the more optimistic the decision maker is about the gains. The interplay between curvature and elevation shapes how probabilities are evaluated and decisions are made, with implications for responses to different risk scenarios. Large losses induce less pessimism than small losses, while heterogeneous losses tend to increase pessimism, underscoring the complex dynamics involved in risk perception and decision-making (Etchart-Vincent 2009).

To put it simply, probability weighting functions incorporate both curvature and elevation, which underlie the psychological and cognitive aspects of probability weighting. Curvature indicates the discriminability between probabilities. The higher the curvature, the more non-linear the function becomes. Meanwhile, elevation represents the attractiveness of a potential gamble, reflecting the degree of optimism. Our approach combines these features of probabilistic sensitivity with the more traditional approach of sensitivity to outcomes. Sensitivity to probabilities is modelled with a probability weighting function, whereas sensitivity to outcomes is modelled with a utility function.

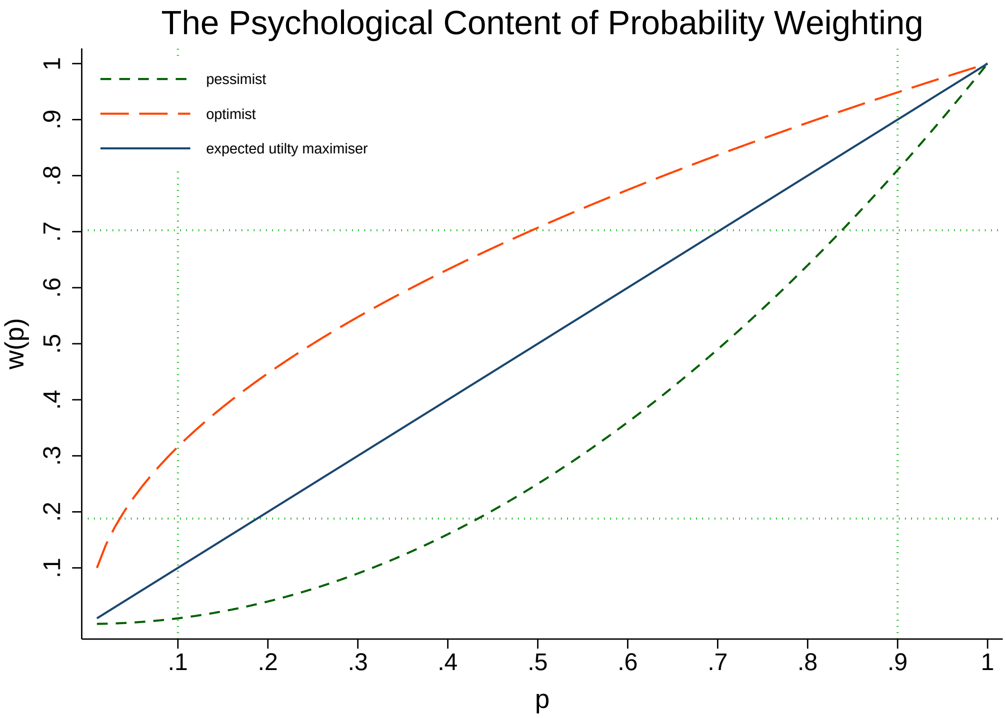

Figure 3: Depiction of elevation for different values of probability weighting

5.2 Feelings and Probability Weighting

The shape of the probability weighting function is influenced by various factors, including the affective nature of the results (as shown in Figure 4) (Pachur, Hertwig & Wolkewitz 2014). Affect-rich outcomes, like achieving a personal milestone, result in distinct probability weighting shapes compared to affect-poor decisions, such as routine financial transactions (Rottenstreich & Hsee 2001). Affect-rich outcomes produce a more S-shaped curve, weighing small probabilities more heavily and larger probabilities less, reducing the sensitivity to intermediate probabilities (Mukherjee 2011). Mood also contributes, with individuals in a good mood more likely to weight gains and less likely to weight losses (Rottenstreich & Hsee 2001). External factors like gender differences play a role, with women's probability weighting curves deviating more from linear weighting than men's curves on average (Bruhin, Fehr-Duda & Epper 2010).

Brandstatter, Kuhberger, and Scheinder (2002) provide a detailed account of emotion and probability weighting. They find that the probability weighting function is influenced by anticipation of elation and disappointment, which are emotional reactions to the outcomes of risky choices (Brandstatter, Kuhberger & Schneider 2002, pp. 1). The authors hypothesise that elation and disappointment are functions of the surprise experienced after winning or losing, respectively, and that surprise is a nonlinear function of the objective probability of the outcome. The authors also assume that disappointment is stronger than elation and that both emotions are weighted by their likelihood of occurrence.

They tested their hypotheses in three experiments. Experiment 1 and 2 measured the surprise, elation, and disappointment ratings of participants who imagined winning or losing different amounts of money with different probabilities. The results supported the non-linearity of the surprise function and the

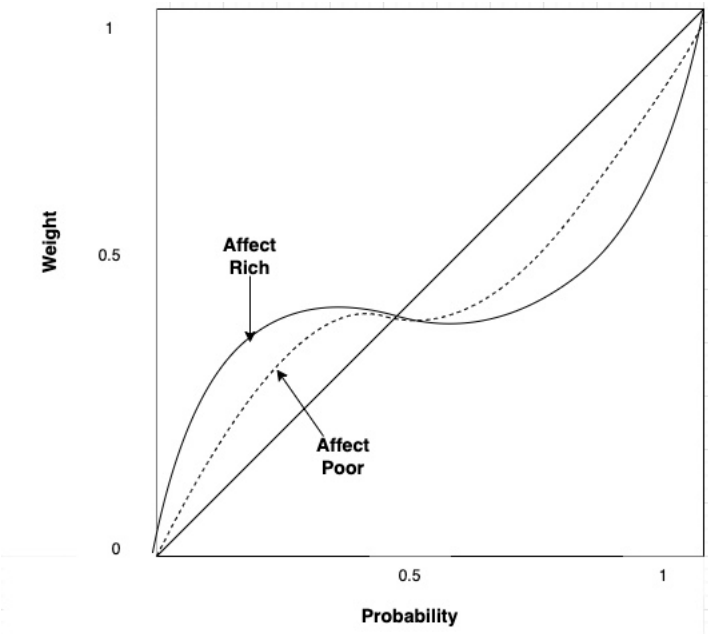

Figure 4: Hypothetical affect-poor and affect-rich weighting functions (and an identity line).

asymmetry of elation and disappointment. Experiment 3 elicited the certainty equivalents of participants who chose between a sure amount and a risky prospect. The results showed that the probability weighting function can be empirically reconstructed from the expected elation and disappointment derived from previous experiments (Brandstatter et al. 2002, pp. 1, 6, 7).

It is hypothesised that outcomes rich in affect elicit higher curvature in probability weighting, while affect-poor outcomes exhibit lower curvature. This affect-driven account of probability weighting suggests that affect-rich outcomes elicit greater degrees of hope and fear and therefore larger jumps at endpoints' (Rottenstreich & Hsee 2001, pp. 186). What about the level of affective thinking of the decision maker? Mukherjee (2011) explores whether the probability weighting function of individuals with high affective thinking orientations systematically differs from those with low affective orientation. It is crucial to consider the dual-system model of human information processing, which comprises two distinct systems: System 1 (the emotional brain) and System 2 (the cognitive brain). System 1 makes rapid decisions based on subjective experiences and evolutionary reasoning, while System 2 is more rational and deliberate. The findings suggest that thinking styles indeed have predictive implications for risky decision-making. Participants with a more affective thinking style, that is, those who rely more on System 1, exhibit a higher curvature in probability weighting and a higher elevation, reflecting greater involvement of anticipated emotions. They find evidence of overweighting small probabilities but no significant differences at high probabilities (Mukherjee 2011, pp. 453).

This paper focusses on negative emotions, such as fear, regret, and anxiety, due to their consistent and profound effects on risk aversion and decision-making quality. Negative emotions are known to increase the sensitivity to potential losses, significantly influencing how people make decisions under uncertainty (Lerner & Keltner 2001). Recent studies further confirm that negative emotions, more than positive ones, lead to more conservative financial decisions and elevated risk aversion (Västfjäll, Slovic, Mayorga & Peters 2016). Given the central role of these emotions in shaping risk-related behaviours, this framework prioritises understanding how fear, regret, and anxiety affect decision making in uncertain contexts.

This study contributes to the literature on decision-making under risk by offering a psychological perspective on the shape of the probability weighting function. Addresses a notable gap in the literature by exploring the impact of emotions on risk preferences in the context of a behavioural intervention. Although previous research has extensively examined the role of emotions in decision-making (Lerner & Keltner 2001, Loewenstein et al. 2001), fewer studies have considered how structured interventions can alter both emotional responses and risk attitudes (Fehr-Duda & Epper 2012, Szasz & Szejniuk 2016).

6 Data

To further investigate the *Risk-as-Feelings* hypothesis, we utilise primary data collected from participants in the *Activate!* programme, introduced earlier. This programme focusses on transforming young people's beliefs and preferences through workshops aimed at fostering self-confidence, goal orientation, creative thinking, and a commitment to the common good. The intervention is designed to improve the confidence, optimism, social cohesion of the participants, work readiness, entrepreneurial spirit, and attitudes towards risk.

The study includes a sample of 427 people aged 20 to 30 years, drawn from marginalised communities throughout South Africa. Participants were selected based on their availability and willingness to participate in the Positive and Negative Affect Schedule (PANAS) survey, which measures emotional states, and a risk elicitation experiment designed to assess their risk preferences. Although participants self-selected into the Activate! programme, they were randomly assigned to one of two groups. The **treatment group** received the intervention in 2014, while the **control group** was scheduled to receive the intervention in 2015. This staggered approach allowed for outcome measurements to be taken at the same time in 2015, after the treatment group had completed the programme but before the control group began.

This staggered design, known as a *delayed treatment control design*, is highly effective in evaluating the effects of the programme. It allows a clear attribution of the observed differences in outcomes to the intervention itself, minimising the influence of external factors or timing discrepancies (Coryn, Noakes, Westine & Schröter 2011, Shadish, Cook & Campbell 2002). Furthermore, this design ensures ethical considerations by eventually offering all participants the intervention, while still allowing comparisons between treated and untreated groups. By adopting this approach, we can confidently attribute systematic differences in risk preferences and emotional states to the effects of the programme, rather than pre-existing conditions or other confounding factors.

Randomisation was tested using two-tailed t tests, which revealed no significant differences between the treatment and control groups on most key variables. As illustrated in Table 2, most risk-related markers are balanced between the treatment and control groups. Although two markers show small differences, these differences are not monotonic and remain minor. Thus, there is no strong evidence to suggest that the treatment and control groups are systematically different. This balance improves the internal validity of the study by ensuring that observed effects are attributable to the programme intervention, rather than pre-existing disparities between groups (Rubin 2008).

Both the PANAS survey and the risk survey were administered in 2015 after the treatment group had completed the intervention but before the control group began theirs. Key outcomes, emotional states, and risk attitudes were only measured at the end of the intervention, without baseline data collected. The underlying assumption of this design is that any systematic differences observed between the treatment and control groups in 2015 can be attributed to the programme, given the randomisation and balance of key variables at the outset.

The PANAS survey was used to assess emotional states, capturing both positive and negative affect. Additionally, a risk elicitation task was conducted to measure participants' risk preferences through a series of hypothetical choices. These endline measurements provide critical insight into how the inter-

Table 1: Summary Statistics

Variable	Control	Treated	Total
Excellent health (1=yes)	0.436	0.433	0.435
Very good health (1=yes)	0.273	0.242	0.259
Good health (1=yes)	0.236	0.281	0.256
Fair health (1=yes)	0.0500	0.0393	0.0452
Poor health (1=yes)	0.00455	0.00562	0.00503
Never exercises (1=yes)	0.105	0.135	0.118
Drinks alcohol very rarely (1=yes)	0.364	0.388	0.374
Drinks alcohol one or two days a week (1=yes)	0.0500	0.112	0.0779
Have had HIV test (1=yes)	0.845	0.893	0.866
Ever engaged in unprotected sex (1=yes)	1.395	1.391	1.393
Totally in control or control over most things in life (1=yes)	0.822	0.801	0.813
Anger (1=never feels angry)	0.212	0.147	0.183
Hostility (1= never feels hostile)	0.538	0.440	0.494
Observations	427		

Notes: Standard deviations in parentheses.

Table 2: Test of Equality of Means

Variable	Difference	t-statistic
Excellent health (1=yes)	0.00378	(0.08)
Very good health (1=yes)	0.0312	(0.70)
Good health (1=yes)	-0.0445	(-1.01)
Fair health (1=yes)	0.0107	(0.51)
Never exercises (1=yes)	-0.0303	(-0.93)
Smoke cigarettes (1=yes)	-0.0843**	(-2.47)
Drinks alcohol one or two days a week (1=yes)	-0.0624**	(-2.32)
Anger (1=never feels angry)	0.0653***	(1.74)
Hostility (1= never feels hostile)	0.0983**	(2.03)
Observations	406	

Notes: t statistics in parentheses. $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

vention influenced participants' emotional states and their risk-taking behaviors.

The responses of the baseline survey help to understand the demographic background and some self-reported risk behaviours of the participants. Table 3 shows the results of the survey. Not all participants answered every question of the survey. The data indicates that most of the participants, 90.62%, identify as Black African. About 26.09% of participants speak IsiZulu as their first language, and 17.85% speak IsiXhosa. The racial and linguistic composition of the sample is broadly similar to that of South Africa, where approximately 81% of the total population is Black African, and nearly 30% speak IsiXhosa or IsiZulu at home. In terms of gender, 54.69% of the surveyed population is male, while 45.31% is female.

Educational attainment in South Africa remains low. In 2018, just over half (51.72%) of participants had completed matric, and 36.84% had received some form of tertiary training. These numbers highlight the gap in educational attainment within the broader South African context, where, nationally, about 59% of individuals aged 25 to 64 have at least completed secondary education (Irwin, Zhang, Wang, Hein, Wang, Roberts, York, Barmer, Bullock Mann, Dilig et al. 2021). With youth unemployment in South Africa expected to be 64.4% in 2019, only 34.32% of the sample reported working for pay, reflecting the economic challenges faced by young people in the country.

Table 3: Summary of Demographic Backgrounds

Variable	n	% Of Total
Gender (1=Male)	239	54.69%
Race (1=African)	396	90.62%
Language: IsiZulu	114	26.09%
Language: IsiXhosa	78	17.85%
Completed Matric (1=yes)	226	51.72%
Completed tertiary training after matric (1=yes)	161	36.84%
Working for pay (1=yes)	150	34.32%
Total	437	100.00%

7 Measurement

7.1 Measuring affect

Participants in both the treatment and control groups were assigned to complete the Short-Form International Positive and Negative Affect Schedule (I-PANASSF). Developed by Thompson (2007), this widely used self-assessment of affect questionnaire is recognised for its validity and consistent interpretation among respondents of diverse cultural backgrounds (Karim, Weisz & Rehman 2011, Merz, Malcarne, Roesch, Ko, Emerson, Roma & Sadler 2013). The questionnaire comprises 10 questions (see Figure 5), half of which assess negative affect, while the remaining half measure positive affect.

The positive affect reflects the desire to experience positive emotions such as *inspired* and *determined*, with higher scores indicating more pronounced positive emotional states. In contrast, negative affect gauges the intensity of negative emotions such as fear, with higher scores indicating more pronounced negative emotional states. Participants expressed their feelings for each I-PANASSF item by selecting a number on the Likert scale ranging from 1 to 5. For this study, we transformed each response into a binary format, encoding a response as 1 if the participant chose "never" and 0 otherwise. This helps to simplify the analysis whilst capturing meaningful differences in affect that is relevant to our research.

As mentioned previously, this study will focus primarily on the analysis of negative emotions.

	Never 1	Rarely 2	Once in a while 3	Sometimes 4	Always 5
Angry	○	○	○	○	○
Hostile	○	○	○	○	○
Ashamed	○	○	○	○	○
Nervous	○	○	○	○	○
Afraid	○	○	○	○	○
Alert	○	○	○	○	○
Attentive	○	○	○	○	○
Determined	○	○	○	○	○
Active	○	○	○	○	○
Inspired	○	○	○	○	○

Figure 5: This scale consists of a number of words that describe different feelings and emotions. Read each item and then mark the appropriate answer in the space next to that word. Indicate to what extent you CURRENTLY feel this way, that is how you feel IN THE MOMENT

7.2 Risk elicitation – Random lottery pairs

Risk attitudes were evaluated using a gambling task, in which participants were required to make choices among lottery pairs. This methodology follows the multiple price list method introduced by (Holt & Laury 2002). This section aims to provide a comprehensive understanding of the rationale behind the use of this method and to elucidate how it was implemented in the programme.

The method employed to elicit risk preferences is a crucial determinant of the reliability of outcomes in this study. Traditional approaches, such as survey questions that seek information about individuals' risk preferences, have shown drawbacks in terms of reliability and effectiveness compared to more robust elicitation methods, as evidenced by previous research (Awa Sanou & Shupp 2018, Holt & Laury 2002). Survey-based approaches often fail to capture accurate risk preferences due to the influence of cognitive biases and contextual factors (Holt & Laury 2002). Furthermore, individuals may not consistently articulate their true risk attitudes when responding to survey questions (Dohmen, Falk, Huffman, Sunde, Schupp & Wagner 2011).

In contrast, the multiple price list (MPL) method offers distinct advantages that mitigate these limitations. This method presents a structured and incentive-driven approach to eliciting risk, reducing the potential for cognitive biases and improving the precision of risk preference measurement (Holt & Laury 2002). The MPL method is renowned in the field of experimental economics for its capacity to generate reliable and consistent data concerning risk attitudes. Specifically, the MPL method excels in diminishing preference reversals, a phenomenon in which individuals make inconsistent choices when assessing risky options (Holt & Laury 2002). The deliberate design of the method and its incentivised nature effectively mitigate these inconsistencies, making it the preferred choice for risk elicitation in experimental settings (Charness & Gneezy 2010).

In addition to its use in monetary decisions, the MPL method has been used as a proxy for non-monetary risk taking behaviours, such as health-related risks or career choices (Anderson & Mellor 2008), because it provides a reliable measure of an individual's general willingness to take risks. Studies have shown that individuals' risk preferences in monetary contexts are often correlated with their risk behaviors in non-monetary domains (Blais & Weber 2006), making the MPL a suitable tool for studying risk-taking beyond purely financial decisions. However, it is important to acknowledge that the MPL, while effective in monetary contexts, may not fully capture the complexities of risk preferences in non-monetary domains, where additional factors like emotional involvement and social consequences may play a significant role (Galizzi & Navarro-Martinez 2016).

Within the study framework of the programmes, participants engaged in tables similar to Table 4, featuring fixed gains with varying probabilities. To ensure robust data collection, each participant interacted with four such tables collectively referred to as "price lists". In each table row, labelled A and B, participants faced a choice between two lotteries. The number of lotteries presented in the table guided their selection. Practice tables were initially provided to acquaint participants with the task.

During the experimental rounds, the participants encountered tables that mirror the structure of Table 4. Each table contained ten outcomes for two lottery options, each with distinct probabilities ranging from 0.1 to 0.9, but with fixed winnings for each set of probabilities. Participants were explicitly instructed to indicate their preferred lottery option (A or B) for each row by circling their choice.

For example, consider row 4 in Table 4, where participants had to choose between option A, which offered an equal chance of winning R138 or R92, and option B, with an equal chance of winning R245 or R31. A risk-seeking person would be drawn to the option with a potentially higher payoff and might lean toward choosing option B more frequently, even though the probability of winning the higher payoff of R245 decreases (rows 4-9), and the expected value (EV) of option A is higher. This inclination comes from their willingness to take risks for the chance of a higher reward. In contrast, a risk-averse individual may be more inclined to choose option A, particularly since the probability of winning a fairly high amount with certainty is greater.

Following completion of the task, each participant had made a total of 40 different lottery selections. The determination of the probability of winning a specific outcome was contingent on the roll of a 10-sided die. For instance, if a participant had chosen lottery A for row 2 from a table similar to Table 1, the potential payoffs for that choice comprised R138 (with a probability of 30%) and R92 (with a probability of 70%). To determine the final outcome, two dice rolls were performed. If a number other than 1 or 2 was generated, the outcome would be R92. In contrast, if a 1 or 2 was rolled, the result would be R138, as these two numbers corresponded to a probability of 30%.

Table 4: Practice round lottery "price" list

Choice	p	x_h^A	$1-p$	x_l^A	p	x_h^B	p	x_l^B	EV(A)	EV(B)	EV(A) − EV(B)
0	0.1	R138	0.9	R92	0.1	R245	0.9	R31	R96	R52	R44
1	0.2	R138	0.8	R92	0.2	R245	0.8	R31	R101	R74	R28
2	0.3	R138	0.7	R92	0.3	R245	0.7	R31	R106	R95	R11
3	0.4	R138	0.6	R92	0.4	R245	0.6	R31	R110	R116	(R6)
4	0.5	R138	0.5	R92	0.5	R245	0.5	R31	R115	R138	(R23)
5	0.6	R138	0.4	R92	0.6	R245	0.4	R31	R119	R159	(R40)
6	0.7	R138	0.3	R92	0.7	R245	0.3	R31	R124	R181	(R57)
7	0.8	R138	0.2	R92	0.8	R245	0.2	R31	R129	R202	(R74)
8	0.9	R138	0.1	R92	0.9	R245	0.1	R31	R133	R224	(R90)
9	1	R138	0	R92	1	R245	0	R31	R138	R245	(R107)

Notes: p is the probability of winning x; x_h^A is the high payoff for lottery A and x_l^A is the low payoff for lottery A; analogously defined for lottery B. EV(A) is the expected value of lottery A, defined analogously for lottery B. The last column is the difference in expected values. Choices are labelled $0-9$ as this is the conventional labelling used on a 10-sided die. Rand values in December 2022 prices.

8 Structural Estimation of Risk Attitudes

To measure risk preferences structurally, we define a constant relative risk aversion (CRRA) as follows:

$$U(x) = \begin{cases} \frac{x^{1-r}}{1-r} & \text{if } x \geq 0, \quad -\infty < r < +\infty, \quad r \neq 1 \\ \ln(x) & \text{if } r = 1 \end{cases} \tag{1}$$

Here, x represents monetary values and r is the risk parameter to be estimated from the data. The coefficient r indicates relative risk aversion, where $r < 0$ for risk seekers, $r = 0$ for risk neutral individuals, and $r > 0$ for risk averse individuals.

We also incorporate a single parameter weighting function utilising the structure proposed by Tversky and Kahneman (1992), denoted as $w(p) : [0, 1] \rightarrow [0, 1]$:

$$w(p) = \frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{\frac{1}{\gamma}}} \tag{2}$$

Here, γ is the shape parameter and p represents the probability of a certain outcome.

It should be noted that the choice of the one-parameter TK probability weighting function was primarily driven by its simplicity and wide acceptance in the field. However, it is subject to criticism for its limited flexibility in capturing all features of the data. For example, the one-parameter model fails to examine curvature and elevation separately, which are crucial components of probability weighting. Critics argue that this limitation hampers a comprehensive understanding of individuals' risk attitudes.

Furthermore, the one-parameter TK model has been criticised for artificially correlating the measure of nonlinearity with the curvature parameter of the utility function. This is because a lower elevation of the probability weighting curve, which indicates stronger concavity, shares similarities with a more concave utility function. Consequently, the model can produce misleading results when assessing risk preferences. Despite its drawbacks we proceed to use the one parameter function because of its ease of use and its empirical robustness and theoretical foundation provide valuable insights into decision-making under uncertainty.

Pairwise Gambles:

In our experimental setup, participants are presented with pairs of gambles or prospects, where one option is riskier than the other. Subjects are asked to choose between these two options. For example, consider the following gambles:

$$\text{Prospect S (safe choice)} = (0.3, 138; 0.7, 92)$$
$$\text{Prospect R (risky choice)} = (0.3, 245; 0.7, 31)$$

If a subject chooses Prospect S, they win 138 with a probability 30% and 92 with a probability 70%. Conversely, if they choose Prospect R, they win 245 with a 30% probability and 31 with a 70% probability. Risk-averse individuals tend to choose Prospect S, while risk-loving subjects opt for Prospect R.

To address potential correlation in the choices made by each individual, we estimate robust standard errors clustered at the individual level. Given that each participant made 40 decision choices, which could be highly correlated, assuming independence among these choices could lead to artificially low standard errors. This could, in turn, increase the likelihood of detecting treatment effects when none exist.

When determining the safe choice, we consider the possibility of computational (Fechner) errors ϵ, where $\epsilon \sim N(0, \sigma^2)$. The safe choice is made if:

$$(U_S) - (U_R) + \epsilon > 0 \tag{3}$$

For each subject, we elicit whether they would choose Prospect S or R when offered pairs of gambles. Consequently, for every subject, we observe a binary outcome of the choice between S and R.

Estimating Model Parameters:

To estimate the model parameters (r and γ), we use the maximum likelihood estimation. Specifically, we maximise the log-likelihood function:

$$\log \mathcal{L} = \sum_{i=1}^{n} \ln \Phi \left[yy_i \times \frac{(U_S) - (U_R) + \epsilon}{\sigma} \right] \tag{4}$$

Here, $yy_i = 1$ if Prospect S is chosen and $yy_i = -1$ if Prospect R is chosen. This function is then solved numerically to estimate the values of r and γ.

In summary, we employ a structural estimation technique to determine the level of relative risk aversion and estimate the curvature of the probability weighting function. This approach allows us to control for individual factors such as gender and affect. In addition, it provides information on the impact of the programme on decision making.

9 Results

9.1 Main Effects

As outlined earlier, our primary hypothesis is rooted in the *Risk-as-Feelings* framework. We hope that participation in the programme will reduce the probability distortions (captured by γ), promoting a more linear probability weighting, indicative of less emotional interference in decision making. Furthermore, we anticipate that the programme will decrease risk aversion (measured by r), particularly by mitigating negative emotions such as fear and nervousness, which are typically associated with higher levels of risk aversion. Thus, we hypothesise that the treatment group will exhibit a lower coefficient of risk aversion (r) and a more linear probability weighting function (reflected in a higher γ value) compared to the control group.

The results obtained from structural estimation of risk aversion levels are shown in Table 6. In all models, the constant is consistently positive and statistically significant. However, the coefficient on *treatment* is not statistically different from zero, indicating that both the control and treatment groups are risk-averse and that the programme did not significantly change risk aversion.

A compelling correlation is revealed in Table 6, Model 8, specifically in relation to the emotional state of *Nervousness* and the risk parameter. Individuals who never experience nervousness have a coefficient of relative risk aversion of $0.164 - 0.119 = 0.045$. This implies that the absence of nervousness corresponds to risk neutrality, while people who feel nervous (some of the time, up to all of the time) are risk-averse ($r = 0.164$), corroborating previous literature associating nervousness with a decreased propensity to risk-taking (Lerner & Keltner 2001). This finding underscores the intricate interplay between emotions and risk preferences (Loewenstein et al. 2001).

Furthermore, gender emerges as a significant factor influencing risk aversion, as evidenced in Model 4 of Table 6. The results highlight a distinct and substantial gender difference, with the coefficient of relative risk aversion (r) for women ($0.135 + 0.139 = 0.274$) exceeding that for men ($r = 0.135$). Essentially, while both genders exhibit risk aversion, females demonstrate a higher degree of risk aversion compared to males. This finding is consistent with the existing literature, which consistently indicates that men tend to exhibit a higher propensity to take risks in various domains (Byrnes, Miller & Schafer 1999). Similarly, studies in financial decision-making show that men are generally more willing to engage in risk-taking behaviour compared to women, regardless of contextual factors such as familiarity or ambiguity (Duda, Gennaro & Schubert 2006).

However, it is important to clarify that the observed gender differences in risk aversion (r) in this study are not directly attributable to differences in *probability weighting*—a concept that affects γ (the curvature of the utility function, particularly with respect to how individuals weigh probabilities), not r. The distinction is crucial because, while probability weighting models how individuals subjectively distort probabilities, the risk aversion coefficient (r) reflects how individuals value outcomes in uncertain situations, independent of how they perceive probabilities.

Empirical studies have shown that women are often more risk averse due to differences in emotion processing and how they respond to risk. For example, women tend to exhibit more pessimistic probability weighting, leading to different risk assessments (Duda et al. 2006). This phenomenon is related to differences in γ, not in r. Therefore, while our findings show a gender difference in risk aversion (r), this is likely due to differences in emotional and cognitive processing between men and women, rather than differences in how they weigh probabilities (Pohl, Bender & Lachmann 2005, Hofer, Siedentopf, Ischebeck, Rettenbacher, Verius, Felber & Fleischhacker 2007). This distinction aligns with research suggesting that gender differences in risk aversion reflect underlying variations in emotion-driven decision-making and risk tolerance.

Table 5: Programme impact on risk attitudes and probability distortion: Main effects

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
r									
Treatment		-0.0540	-0.00172	0.00286	0.00320	-0.00133	0.00367	-0.0142	0.00529
		(0.0543)	(0.0506)	(0.0510)	(0.0508)	(0.0512)	(0.0525)	(0.0517)	(0.0519)
Female (1=yes)				0.139***	0.141***	0.135***	0.146***	0.131**	0.150***
				(0.0513)	(0.0519)	(0.0507)	(0.0539)	(0.0513)	(0.0524)
Anger (1=never feels angry)					0.0345				
					(0.0689)				
Hostility (1=never feels hostile)						-0.0499			
						(0.0502)			
Shame (1=never feels shame)							0.0419		
							(0.0538)		
Nervousness (1=never feels nervous)								-0.119*	
								(0.0683)	
Fear (1=never feels fearful)									0.0167
									(0.0562)
Constant	0.182***	0.217***	0.190***	0.135***	0.127***	0.163***	0.113**	0.164***	0.124***
	(0.0285)	(0.0397)	(0.0326)	(0.0398)	(0.0424)	(0.0506)	(0.0461)	(0.0440)	(0.0436)
μ									
Constant	0.186***	0.186***	0.185***	0.178***	0.178***	0.178***	0.178***	0.179***	0.180***
	(0.0112)	(0.0114)	(0.0113)	(0.0110)	(0.0110)	(0.0110)	(0.0110)	(0.0116)	(0.0113)
γ									
Treatment			0.266***	0.300***	0.292***	0.297***	0.294***	0.276***	0.290***
			(0.0942)	(0.0940)	(0.0955)	(0.0955)	(0.0954)	(0.0942)	(0.0938)
Female (1=yes)				-0.0720	-0.0704	-0.0764	-0.0635	-0.0907	-0.0877
				(0.0852)	(0.0856)	(0.0847)	(0.0904)	(0.0887)	(0.0865)
Anger (1=never feels angry)					-0.0792				
					(0.0941)				
Hostility (1=never feels hostile)						-0.0142			
						(0.0836)			
Shame (1=never feels shame)							-0.138		
							(0.0888)		
Nervousness (1=never feels nervous)								-0.227**	
								(0.0966)	
Fear (1=never feels fearful)									-0.254***
									(0.0861)
Constant	0.766***	0.772***	0.663***	0.679***	0.699***	0.688***	0.744***	0.747***	0.785***
	(0.0394)	(0.0439)	(0.0458)	(0.0601)	(0.0689)	(0.0829)	(0.0758)	(0.0745)	(0.0794)
Observations	15463	15183	15183	14503	14503	14503	14503	14503	14503

Notes: Standard errors in parentheses. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$. Top panel shows estimates of the coefficient of relative risk aversion r, where $r = 0$ implies risk neutrality, $r > 0$ implies risk aversion, and $r < 0$ implies risk-seeking. Bottom panel shows propensity for probability distortion, γ, modelled with the non-linear probability weighting $w(p) = \frac{p^\gamma}{(p^\gamma+(1-p)^\gamma)^{\frac{1}{\gamma}}}$, where $\gamma = 1$ implies no distortion and $0.279 < \gamma < 1$ implies a propensity to distort probabilities.

Table 6: Programme impact on risk attitudes and probability distortion: main effects

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
r									
Treatment		-0.0540	-0.00172	0.00286	0.00320	-0.00133	0.00367	-0.0142	0.00529
		(0.0543)	(0.0506)	(0.0510)	(0.0508)	(0.0512)	(0.0525)	(0.0517)	(0.0519)
Female (1=yes)				0.139***	0.141***	0.135***	0.146***	0.131**	0.150***
				(0.0513)	(0.0519)	(0.0507)	(0.0539)	(0.0513)	(0.0524)
Anger (1=never feels angry)					0.0345				
					(0.0689)				
Hostility (1= never feels hostile)						-0.0499			
						(0.0502)			
Shame (1= never feels shame)							0.0419		
							(0.0538)		
Nervousness (1= never feels nervous)								-0.119*	
								(0.0683)	
Fear (1= never feels fearful)									0.0167
									(0.0562)
Constant	0.182***	0.217***	0.190***	0.135***	0.127***	0.163***	0.113**	0.164***	0.124***
	(0.0285)	(0.0397)	(0.0326)	(0.0398)	(0.0424)	(0.0506)	(0.0461)	(0.0440)	(0.0436)
mu									
Constant	0.186***	0.186***	0.185***	0.178***	0.178***	0.178***	0.178***	0.179***	0.180***
	(0.0112)	(0.0114)	(0.0113)	(0.0110)	(0.0110)	(0.0110)	(0.0110)	(0.0116)	(0.0113)
gamma									
Treatment			0.266***	0.300***	0.292***	0.297***	0.294***	0.276***	0.290***
			(0.0942)	(0.0940)	(0.0955)	(0.0955)	(0.0954)	(0.0942)	(0.0938)
Female (1=yes)				-0.0720	-0.0704	-0.0764	-0.0635	-0.0907	-0.0877
				(0.0852)	(0.0856)	(0.0847)	(0.0904)	(0.0887)	(0.0865)
Anger (1=never feels angry)					-0.0792				
					(0.0941)				
Hostility (1= never feels hostile)						-0.0142			
						(0.0836)			
Shame (1= never feels shame)							-0.138		
							(0.0888)		
Nervousness (1= never feels nervous)								-0.227**	
								(0.0966)	
Fear (1= never feels fearful)									-0.254***
									(0.0861)
Constant	0.766***	0.772***	0.663***	0.679***	0.699***	0.688***	0.744***	0.747***	0.785***
	(0.0394)	(0.0439)	(0.0458)	(0.0601)	(0.0689)	(0.0829)	(0.0758)	(0.0745)	(0.0794)
Observations	15463	15183	15183	14503	14503	14503	14503	14503	14503

Notes: Standard errors in parentheses. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$. Top panel shows estimates of the coefficient of relative risk aversion r, where $r = 0$ implies risk neutrality, $r > 0$ implies risk aversion, and $r < 0$ implies risk seeking. Bottom panel shows propensity for probability distortion, γ, modelled with the non-linear probability weighting $w(p) = \frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{\frac{1}{\gamma}}}$ where $\gamma = 1$ implies no distortion and $0.279 < \gamma < 1$, implies propensity to distort probabilities.

Despite these insights into risk aversion, the results reveal strong evidence of treatment effects on probability distortion (γ). In contrast to risk aversion, the *treatment* variable significantly affects the propensity to distort probabilities. In all models, the parameter γ indicates that programme participants act more like expected utility maximisers, with a γ estimate of 1.05, compared to the control group's γ of 0.784. This result suggests that the Activate! programme attenuates emotional biases in probability assessment, fostering more rational decision making.

9.2 Potential Mechanisms

To explore how the programme shapes individuals' perceptions of risk, we employ a comprehensive econometric framework, combining Probit analysis and maximum likelihood estimation (ML). This approach allows us to model the intricate interplay between emotions and risk attitudes.

The programme delivered a series of workshops aimed at instilling confidence and optimism in young adults, anticipating a positive impact on affect (Keswell & Burns 2023). Elevated self-confidence and increased self-esteem can bolster emotions by fostering feelings of security, well-being, and positivity. Individuals with greater self-confidence tend to approach challenges with a positive attitude, resulting in a reduction in stress, anxiety, and negative emotions (Cast & Burke 2002). In contrast, low self-confidence and self-doubt can cause negative emotions such as anxiety, fear, and shame. Cast and Burke (2002) argue that individuals with high self-esteem experience fewer negative emotions compared to those with low self-esteem.

Firstly, we employ a Probit model to investigate the relationship between the binary outcome variable *Affect*, where a value of 1 represents the absence of a specific emotion (e.g., anger, indicating that the participant has not recently experienced extreme levels of anger) and the treatment variable, *Treatment*.

$$\Pr(affect_i = 1) = \Phi(\beta_0 + \beta_1 \cdot \text{treatment}_i) \tag{5}$$

where:

$\Pr(affect_i)$ represents the probability that individual i has not recently experienced the specific emotion

$\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution.

β_0 is the intercept of the Probit model.

β_1 is the coefficient associated with the *Treatment* variable

After estimating the Probit model, we calculate marginal effects to assess the intervention's impact on affect, particularly on the likelihood of not experiencing the emotion. We evaluated the effect of the programme on both negative and positive emotions. Table 7 shows the programme's impact on negative emotions. The Probit index coefficients provide the correct sign and significance for each negative emotion outcome.

In particular, two significant effects emerge on anger and hostility. These emotions are reverse coded; thus, a positive index implies that the treatment increases the probability of not experiencing the emotion, while a negative index suggests the opposite effect. We interpret the first column in Table 7 on anger as programme participants being 19% less likely not to experience anger compared to non-participants. Similarly, participants are almost twice less likely not to experience hostility relative to non-participants. Given the significance of this result, it is unlikely that the observed effects on anger and hostility are random and can be attributed to treatment. The programme appears to decrease the probability of never feeling anger or hostility.

However, there were no similarly significant effects on positive emotions. Given the significant effect

Table 7: Programme impact on potential mediators: negative emotions

	Anger	Hostility	Shame	Nervousness	Fear
-					
Marginal Effect	0.19211	0.50000	0.43947	0.15526	0.28947
Se	0.02039	0.02554	0.02557	0.01850	0.02296
Z	9.42060	19.57633	17.18686	8.39219	12.60680
P Value	0.00000	0.00000	0.00000	0.00000	0.00000
Ci					
lower limit	0.15214	0.44994	0.38936	0.11900	0.24447
upper limit	0.23207	0.55006	0.48959	0.19152	0.33448
Probit index					
Treatment	-0.269*	-0.256**	-0.0956	-0.119	-0.150
	(0.154)	(0.130)	(0.131)	(0.158)	(0.137)
Constant	-0.761***	0.111	-0.111	-0.964***	-0.491***
	(0.0967)	(0.0863)	(0.0863)	(0.101)	(0.0873)
Observations	15200	15200	15200	15200	15200

Notes: This table shows the marginal effect of the treatment on five different negative affect measures: Anger, Hostility, Shame, Nervousness, and Fear. Each row shows the estimated marginal effect of the treatment on one negative affect measure. The marginal effect column shows the estimated effect size, which ranges from 0 to 1. The standard errors (Se) and Z-scores are also displayed.

of anger and hostility, these two emotions are the only candidates to investigate as potential mechanisms, as examined in Tables 8 and 9 below. Both tables show that the interaction effect of treatment with anger (Model 5) and hostility (Model 6) is not significant in regression r or γ. Although it is unclear why the programme caused participants to become more angry or hostile, it is important to note that negative emotions do not explain the programme's observed effect on probability distortions.

Table 9 presents the results of the models used to examine the potential mechanisms through which the programme impacts the probability distortion. Across all models in Table 9, there is significant evidence of strong treatment effects on probability distortion. Visualizing this graphically in Figure 6, it is evident that programme participants behave like expected utility maximizers. The treatment group has a γ value of 1.05, compared to the control group with a γ value of 0.784. Thus, the programme attenuates probability distortion. This suggests that the psychological dispositions that influence probability distortions could have been altered for the programme participants by the end of the programme.

The correlation of fear and nervousness with probability distortion is intriguing. Initially, our hypothesis suggested that people experiencing negative emotions would demonstrate a more pessimistic risk assessment (Fehr-Duda & Epper 2012). However, examining the results of Model 3 in Table 9 uncovers an unexpected correlation between *absence* of nervousness and a more pronounced S-shaped probability weighting function for the control group. This is evidenced by a lower estimate of γ of 0.57 (0.762 - 0.194), indicating a stronger curvature in the probability weighting function. Similarly, in Model 4, the coefficient on fear is negative and significant, resulting in a lower estimate of $\gamma = (0.791 - 0.20) = 0.58$, indicating a more pronounced S-shaped probability weighting function for subjects in the control group who never experience fear.

These results suggest that fear and nervousness may act as regulatory mechanisms on probability distortions. Surprisingly, individuals who do not experience these emotions seem more likely to exhibit distorted probability weighting, indicating overoptimism or exaggerated responses to low probability outcomes. This finding diverges from conventional theories that posit negative emotions, such as fear,

Table 8: Programme impact on risk attitudes: potential mechanisms

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
r							
Treatment	-0.00241	-0.000543	-0.0136	-0.0111	-0.0517	-0.0443	-0.0517
	(0.0513)	(0.0523)	(0.0517)	(0.0524)	(0.0551)	(0.0738)	(0.0716)
Female (1=yes)	0.139***	0.143***	0.133**	0.136**	0.147***	0.140**	0.147***
	(0.0512)	(0.0546)	(0.0543)	(0.0551)	(0.0564)	(0.0561)	(0.0565)
Anger (1=never feels angry)	0.0662	0.0508	0.0557	0.0501	-0.0440	0.0516	-0.0440
	(0.0784)	(0.0776)	(0.0737)	(0.0783)	(0.0800)	(0.0794)	(0.0831)
Hostility (1= never feels hostile)	-0.0667	-0.0772	-0.0549	-0.0569	-0.0573	-0.0879	-0.0573
	(0.0552)	(0.0581)	(0.0590)	(0.0602)	(0.0588)	(0.0753)	(0.0750)
Shame (1= never feels shame)		0.0572	0.0675	0.0630	0.0656	0.0631	0.0656
		(0.0570)	(0.0560)	(0.0570)	(0.0567)	(0.0573)	(0.0570)
Nervousness (1= never feels nervous)			-0.137*	-0.156**	-0.138*	-0.156**	-0.138*
			(0.0756)	(0.0740)	(0.0737)	(0.0747)	(0.0751)
Fear (1= never feels fearful)				0.0401	0.0275	0.0406	0.0275
				(0.0612)	(0.0620)	(0.0617)	(0.0624)
Treatment X anger					0.244		0.244
					(0.156)		(0.166)
Treatment X hostility						0.0683	-0.000103
						(0.106)	(0.112)
Constant	0.158***	0.139***	0.153***	0.147***	0.162***	0.162***	0.162***
	(0.0514)	(0.0533)	(0.0527)	(0.0532)	(0.0529)	(0.0580)	(0.0558)
mu							
Constant	0.178***	0.178***	0.178***	0.178***	0.178***	0.178***	0.178***
	(0.0110)	(0.0110)	(0.0116)	(0.0118)	(0.0118)	(0.0118)	(0.0118)
Observations	14503	14503	14503	14503	14503	14503	14503

Notes: Standard errors in parentheses. $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$. Table shows estimates of the coefficient of relative risk aversion r, where $r = 0$ implies risk neutrality, $r > 0$ implies risk aversion, and $r < 0$ implies risk-seeking.

Table 9: Programme impact on probability distortions: potential mechanisms

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
gamma							
Treatment	0.289***	0.291***	0.275***	0.275***	0.265***	0.259**	0.266**
	(0.0962)	(0.0970)	(0.0966)	(0.0966)	(0.101)	(0.128)	(0.125)
Female (1=yes)	-0.0753	-0.0718	-0.0895	-0.106	-0.100	-0.105	-0.100
	(0.0854)	(0.0918)	(0.0945)	(0.0955)	(0.0955)	(0.0959)	(0.0963)
Anger (1=never feels angry)	-0.0687	-0.0339	-0.0166	0.0242	0.00423	0.0278	0.00399
	(0.103)	(0.102)	(0.0997)	(0.103)	(0.105)	(0.104)	(0.107)
Hostility (1= never feels hostile)	-0.00280	0.0141	0.0467	0.0515	0.0573	0.0393	0.0580
	(0.0900)	(0.0973)	(0.0980)	(0.0971)	(0.0952)	(0.115)	(0.111)
Shame (1= never feels shame)		-0.122	-0.0960	-0.0336	-0.0314	-0.0310	-0.0314
		(0.0965)	(0.0959)	(0.0988)	(0.0986)	(0.0994)	(0.0990)
Nervousness (1= never feels nervous)			-0.194*	-0.136	-0.130	-0.138	-0.130
			(0.102)	(0.104)	(0.104)	(0.105)	(0.104)
Fear (1= never feels fearful)				-0.208**	-0.207**	-0.208**	-0.207**
				(0.0981)	(0.0956)	(0.0979)	(0.0956)
Treatment X anger					0.113		0.114
					(0.316)		(0.329)
Treatment X hostility						0.0350	-0.00238
						(0.189)	(0.194)
Constant	0.700***	0.740***	0.762***	0.791***	0.785***	0.798***	0.784***
	(0.0852)	(0.0872)	(0.0897)	(0.0925)	(0.0907)	(0.100)	(0.0971)
Observations	14503	14503	14503	14503	14503	14503	14503

Notes: Standard errors in parentheses. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$. Table shows propensity for probability distortion, γ, modelled with the non-linear probability weighting $w(p) = \frac{p^{\gamma}}{(p^{\gamma}+(1-p)^{\gamma})^{\frac{1}{\gamma}}}$ where $\gamma = 1$ implies no distortion and $0.279 < \gamma < 1$, implies propensity to distort probabilities.

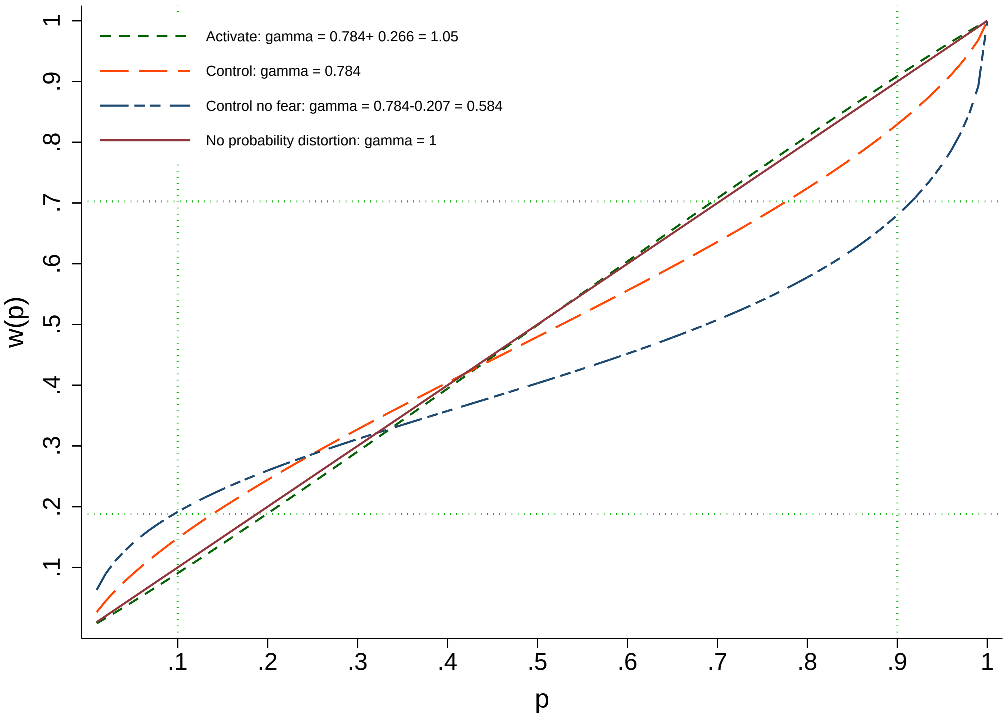

Figure 6: Fitted Probability Weighting Functions by Treatment Condition

Notes: The figure shows propensities to distort probabilities by treatment condition. γ, modelled with the non-linear probability weighting $w(p) = \frac{p^{\gamma}}{(p^{\gamma}+(1-p)^{\gamma})^{\frac{1}{\gamma}}}$, where $\gamma = 1$ implies no distortion and $0.279 < \gamma < 1$, implies propensity to distort. The estimates of γ are based on model 7 of Table 9.

as drivers of pessimism and distorted risk perception.

10 Conclusion

This study has provided valuable insights into the relationship between affective states, risk attitudes, and probability distortion within the context of the *Activate!* intervention. By exploring how emotions influence individuals' perception of risk, we emphasise the importance of understanding emotional influences in decision-making, particularly in risky scenarios.

Supporting Loewenstein's (2000) *Risk-as-Feelings* hypothesis, our findings confirm that emotions play a significant role in shaping risk perceptions and choices. Although both the control and treatment groups exhibit risk aversion, the programme does not change this trend. However, significant effects were observed regarding probability distortion, suggesting the programme helps participants behave in ways more aligned with expected utility maximization. Interestingly, the programme reduces the likelihood that participants never experience anger or hostility, although this does not fully explain the observed changes in probability distortion. In addition, those who never experience nervousness tend toward risk neutrality, while nervous and fearful individuals exhibit greater risk aversion and distorted risk perceptions.

The study also highlights gender differences, with women displaying greater risk aversion, suggesting that future interventions should consider tailoring approaches to account for gender-specific emotional processing.

Our study has several limitations. The tasks used may not fully reflect risk in real-world settings, and the sample may not be representative of all young adults. Furthermore, the absence of baseline data limits our ability to assess changes over time. Future research should explore more ecologically valid tasks and track emotional changes and risk attitudes longitudinally to improve generalisability. Exploring the long-term impacts of interventions on behaviours such as entrepreneurship or substance use would also provide deeper insights into the effectiveness of programmes like *Activate!*.

Although the primary focus of this study is on negative emotions such as fear and nervousness, which are known to amplify risk aversion, the programme was also expected to foster positive emotions such as well-being and security. These positive emotions, which were measured but not analysed in detail here, could play an important role in compensating for negative emotional impacts on risk-taking. Future research should investigate the potential mitigating effects of positive emotions on risk aversion and probability distortion.

Further research could examine the mechanisms underlying probability distortion more thoroughly, focusing on aspects like the curvature and elevation of probability weighting, potentially by exploring differences in thinking styles between participants and non-participants. Furthermore, testing hypotheses related to self-confidence and its impact on decision making in risky situations, as well as validating findings on fear and nervousness, would contribute to a stronger understanding of the effects of the intervention.

Looking forward, exploring the cultural, social, and demographic factors influencing affective states and decision-making will provide a more comprehensive understanding of risk-taking behaviors. This will help tailor future interventions to better address emotional and psychological dimensions of risky behaviors.

In conclusion, this study underscores the crucial role of emotions in the design of effective interventions to mitigate risky behaviours. By integrating insights from psychology, neuroscience, and behavioral economics, interventions can more effectively address emotional aspects of decision making, leading to improved public health outcomes and well-being.

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