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Ph.D. THESIS SUMMARY

THE IMPACT OF RESPONSE EXPECTANCIES ON POSITIVE EMOTIONAL FUNCTIONING: THEORETICAL AND PRACTICAL IMPLICATIONS

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Notes.

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TABLE OF CONTENTS

Key words: response expectancy, positive emotions, relaxation, optimism, positive intervention

CHAPTER I. THEORETICAL BACKGROUND

Response Expectancy Theory

Response expectancies were first conceptualized by Kirsch in 1985 as a distinct type of expectancy not previously recognized in the literature (Bandura, 1977; Rotter, 1954). This specific form of expectancy pertains to individuals' anticipations of their automatic and non-volitional reactions to stimuli or behaviours, such as expecting to become anxious during an interview or to relax during a walk. These expectancies significantly enhance the likelihood of experiencing these specific emotions in given contexts, offering a critical lens to understand human responses.

According to Response Expectancy Theory (Kirsch, 1985, 1990), response expectancies directly determine non-volitional outcomes, operate independently of other psychological mediators, and are self-confirming, meaning they inherently reinforce the behaviours or reactions they anticipate. Kirsch (1985) described non-volitional responses as occurring "automatically, without volitional effort." The non-volitional responses include a range of automatic reactions and experiences, from emotional reactions such as fear or relaxation to physiological responses like blushing or sexual arousal to subjective sensations such as pain or fatigue. The mechanisms through response expectancies directly influence the experiences are based on the premise that "the perception is not just of the experience, it is the experience" (Kirsch, 2000, p. 280). This concept is rooted in monist theories of the mind-body connection (Kirsch & Hyland, 1987), which sustain a direct association between cognitions and physical states (Kirsch, 2000). As a result, subjective states can induce corresponding objective reactions; for example, expecting to feel alert after consuming decaffeinated coffee has been associated with an increase in blood pressure (Kirsch, 1997). Similar to the way emotions are generated naturally by related beliefs (e.g., experiencing relaxation corresponds with calm thoughts), and voluntary intentions automatically result in responses (e.g., standing up is directly associated with the intention of standing), the response expectancy is sufficient to generate the corresponding experience. The concept of automaticity originates from the activation of schemas (Kirsch & Lynn, 1998). Cognitive schemas are systematic structures of knowledge that assist in interpreting and perceiving inputs (Lynn et al., 2019, 2023). Kirsch and Lynn (1998) propose that patients' response expectancies could act as triggers that prompt the activation of specific schemas in response to environmental stimuli.

The relevance of response expectancy in influencing non-volitional outcomes has been demonstrated across various contexts. For instance, in the field of hypnosis, response expectancy plays an important role in determining the depth of the hypnotic state and the effectiveness of hypnotic suggestions (Lynn et al., 2019, 2023). Research in the placebo domain has shown that patients' expectancies can lead to physiological and psychological improvements even in the absence of active treatment (Ballou et al., 2017; Kirsch, 2013; Kube et al., 2021; Leibowitz et al., 2019). Furthermore, response expectancies have been shown to impact the efficacy of treatments in various medical fields, including pharmacological agents and psychotherapy (Evers et al., 2019; Faria et al., 2017; Kirsch, 2015, 2019; Kirsch et al., 2016; Rutherford et al., 2017). More specifically, response expectancies have been proven to influence the occurrence and severity of treatment side effects (Devlin et al., 2017, 2019, 2020; Fletcher et al., 2018; Sullivan et al., 2011), pain management (Peerdeman et al., 2016; Vase et al., 2015) and emotional responses (e.g., Cristea et al., 2011; Dilorenzo et al., 2011; Montgomery et al., 2007).

Existing studies typically investigate the relation between response expectancies and nonvolitional outcomes using correlational methods to assess the association between expectancies and outcomes. According to the response expectancy theory, these expectancies are considered accurate. Several meta-analyses have revealed a moderate correlation between response expectancies and various side effects in the context of cancer treatments (Sohl et al., 2009) found $r = 0.36$; Fletcher et al., 2018 found ranges from $r = 0.21$ to 0.47; Devlin et al., 2017 found $r = 0.26$). Additionally, Coteţ and David (2016) reported a moderate positive association between response expectancies and emotional outcomes ($r = 0.46$).

Kirsch (1985) argued that the impact of response expectancies on non-volitional responses depends on two key factors: the strength of the expectancy and the magnitude of the expected change. Therefore, if an individual has a weak expectancy for a substantial change in their emotional state, the correlation between these two factors is likely very weak. Conversely, if an individual holds a strong expectancy for a minor change in emotional outcome, the relationship between these two factors should be strong (Kirsch, 1985). Kirsch further noted that expectancies that are temporally closer to the event they pertain tend to be more accurate. Moreover, having prior experience with an event can lead to more accurate expectations about specific reactions in that context (Kirsch, 1985, 1990). These insights suggest that stronger expectancies directly influence outcomes and produce more precise anticipatory responses.

Response Expectancies and Related Constructs

Generalized Expectations for the Future

Response expectancies, operationalized as situation-specific anticipations, have been found to correlate with the *optimism-pessimism disposition*, which represents generalized expectations for the future (Carver & Scheier, 2014). Several studies have suggested that response expectancies for negative emotions are negatively correlated with optimism and positively correlated with pessimism (Cristea et al., 2011; Dilorenzo et al., 2011; Montgomery & Bovbjerg, 2004; Podina & Vîslă, 2014; Sohl et al., 2012). Conversely, response expectancies for relaxation are positively associated with optimism and negatively associated with pessimism (Dilorenzo et al., 2011). Moreover, research has shown that response expectancies and the optimism-pessimism disposition interact to shape emotional reactions (Geers et al., 2005, 2007; Geers & Lassiter, 2002; Kern et al., 2020). This interactionist perspective suggests that optimism-pessimism can significantly moderate the relationship between response expectancies and affective experiences.

Response hope

Response hope is the desire for a specific non-volitional outcome to occur in a particular situation, affecting a range of emotional states or physical sensations such as distress or relaxation (Anton & David, 2013; David et al., 2006). Previous studies have shown that individuals with higher response expectancy tend also to have higher levels of response hope (Montgomery et al., 2003). Despite their close relationship, response hope and response expectancy are distinct concepts, each with its predictive power (David et al., 2004, 2006; Montgomery et al., 2003). For example, an individual may expect to feel anxious during a public speech but may also hope to remain confident and calm during the presentation.

More than this, David and colleagues (2006) developed the concept of a discrepancy score to illustrate how differences between an individual's response hope and response expectancy can impact their emotional reactions. They define this score by subtracting an individual's response expectancy from their response hope. For example, if an individual attends a social gathering hoping to feel very safe but expects to feel very little safe, the resulting discrepancy score would be positive. This positive discrepancy score between response hope and response expectancy regarding a positive emotion would likely lead to a low level of positive emotions or a high level of distress for the individual (i.e., the individual will be highly dissatisfied in a situation where expectations are far from desires). Conversely, if an individual hopes to feel little safety at a social gathering but expects to feel very safe, the discrepancy score would be negative. This negative discrepancy score between response hope and response expectancy regarding a positive emotion would likely result in a high level of positive emotions or low distress (i.e., the individual will be extremely satisfied in a situation where expectations far exceed hopes (Anton & David, 2013; David et al., 2006).

Response Expectancies and Emotional Outcomes

A review of response expectancy theory, which explores emotional outcomes, suggests that positive and negative affect are influenced by corresponding expectancies (Cristea et al., 2011; David et al., 2006; Dilorenzo et al., 2011; Kirsch, 1997; Montgomery et al., 2007). For instance, the expectancy of anxiety before an exam was positively associated with distress experienced right before the exam, whereas the expectancy for relaxation correlated with a relaxation response during the event (David et al., 2006). Conversely, response expectancies have been shown to accurately predict emotional non-volitional outcomes in both cross-sectional and experimental research (Cristea et al., 2011; Geers & Lassiter, 2002; Montgomery et al., 2007; Podina & Vîslă, 2014; Vîslă et al., 2013). Additionally, a meta-analysis by Coteţ and David (2016) found a moderate effect size for the association between expectancies and negative emotions ($r = 0.46$) and positive emotions ($r = 0.39$).

Coteţ and David (2016) proposed a comprehensive model for response expectancy that includes affective forecasts as a type of these expectancies, focusing on emotional predictions. The principal argument for this unified model was that both theories postulated a relation between emotional predictions and experienced emotions. Affective forecasts involve predictions that individuals make about their future emotional responses to various life events, a line of research in social psychology (Klaaren et al., 1994). According to the affective forecasting approach (Gilbert et al., 1998; Gilbert & Wilson, 2007, 2009), there is often a discrepancy between emotional predictions and actual emotional responses during various life events. Specifically, individuals frequently overestimate or mispredict their emotional reactions to specific situations (e.g., Buechel et al., 2014; Carlson et al., 2023; Dunn et al., 2007; Levine et al., 2012). The methodology commonly used in affective forecasting research involves calculating the average differences between predicted emotions and the emotional experiences reported. Additionally, many studies also report the correlation between forecasts and actual emotions. On the contrary, the methodology used in response expectancy research is based on correlations between the predictions and emotional experiences. Although different theoretical assumptions and methodologies shape each area of research, the relationship between expectations and experienced emotions remains a central focus of study for both lines of research. Within the response expectancy framework, expectancies are considered accurate predictors of nonvolitional outcomes due to their close association with these outcomes. Conversely, the affective forecasting approach often views predictions as inaccurate, primarily because they tend to differ in intensity from the actual emotional outcomes. In this context, two types of accuracy in emotional prediction have been distinguished: relative accuracy and absolute accuracy (Mathieu & Gosling, 2012). *Relative accuracy* assesses the correlation between predictions and emotions in the response expectancy paradigm, where predictions are considered relatively accurate if individuals who anticipate more intense emotions experience them as such, and vice versa. On the other hand, absolute accuracy refers to the numerical difference between predicted and actual emotions, as examined in the affective forecasting approach, highlighting the discrepancy between predicted and experienced. Two meta-analyses (Coteţ & David, 2016; Mathieu & Gosling, 2012) showed that relative accuracy is high in emotional predictions, meaning individuals who predict more intense emotions tend to experience them as such. However, absolute accuracy is low, indicating that individuals generally overestimate their future emotional states.

In the present thesis, our primary focus is investigating the accuracy of emotional predictions in a relative sense. This research focus is grounded in the theoretical assumptions proposed by the response expectancy theory, which suggests a causal relationship between expectancies and emotional outcomes (Kirsch, 1985, 1990).

Response Expectancies and Positive Emotions: A Major Gap

Despite the increased interest in the role of response expectancy in influencing emotional outcomes, important gaps remain in the empirical research. The significant limitation we identified in the literature on response expectancy and emotional outcomes is the disproportionate number of studies investigating this relationship. In contrast to the numerous studies examining the relationship between response expectancy and negative emotions, only a few have focused on exploring this relationship in the context of positive emotions (Cotet & David, 2016). Addressing this gap is important for conceptually understanding how response expectancies influence positive emotions, which could improve therapeutic interventions to promote well-being and mental health. Historically, research has primarily concentrated on negative emotions and pathology, with less attention given to positive emotions and well-being (Alexander et al., 2021). Consequently, gaining a deeper understanding of positive emotions is just as important as understanding and mitigating negative ones (Pavic et al., 2022).

Positive Emotions

Emotions are often conceptualized along two dimensions: positive versus negative valence, and high versus low levels of activation (Russell, 1980). Positive emotions, therefore, encompass pleasant or desirable reactions to situational stimuli (Heyn et al., 2021). According to the Broaden-and-Build theory, positive emotions enable individuals to develop psychological, intellectual, and social resources while expanding their repertoire of thoughts and actions (Fredrickson, 2001, 2013; Shiota et al., 2017). Additionally, positive emotions can prevent experiencing acute psychological stress symptoms (Zander-Schellenberg et al., 2020), buffer against adverse health outcomes (van Steenbergen et al., 2021), and contribute to improved health (Behnke et al., 2023; Jones & Graham-Engeland, 2021; Steptoe, 2018).

Although there has been increased attention to positive emotions in clinical research, significant gaps remain. One primary issue is the unequal attention given to different types of emotional arousal in studies. High arousal positive emotions (HAPA), such as being active, alert, and excited, are frequently featured in measures like the Positive and Negative Affect Schedule's Positive Affect subscale (Watson et al., 1988). In contrast, low arousal positive affect (LAPA), which includes feelings of calm, relaxation, and contentment, receives comparatively less attention in research on positive affectivity (Fredrickson et al., 2008; McManus et al., 2019). Furthermore, the mechanisms underlying the experience of both high and low arousal positive emotions require more rigorous and systematic investigation. Existing research, including cross-sectional studies (e.g., Chanel et al., 2023; Cristea et al., 2011; Feys & Anseel, 2015; Levine et al., 2012) and a limited number of experimental studies (e.g., Geers & Lassiter, 2002), has supported the relationship between response expectancy and positive emotions. More comprehensive experimental and longitudinal studies are needed in this area to advance our understanding.

Other Limitations in Response Expectancy Research

The *second* significant limitation relates to the types of studies conducted; most are correlational, which constrains our understanding of causal relationships and the complex dynamics between individuals' response expectancies and positive emotional outcomes. To overcome these limitations, it is crucial to incorporate longitudinal studies, as previously suggested (Podina & Visla, 2014; Visla et al., 2013), to monitor the relationship between response expectancy and positive emotions over time. This approach will enable a more comprehensive understanding of changing and consistent patterns in how expectancies influence emotions, thus clarifying the development of these relationships over time. Furthermore, it is essential to conduct experimental research to confirm the causal links suggested by correlational studies. By manipulating response expectancies in controlled and ecological contexts, researchers can clarify the extent to which expectancies can influence emotional states across different scenarios.

The *third* major limitation pertains to how the response expectancy construct is measured. Kirsch (1985) stated that the "probability of a nonvolitional response varies directly with the strength of the expectancy of its occurrence and inversely with the magnitude or difficulty of the expected response" (p. 1199), introducing two dimensions of response expectancy. The *expected magnitude* relates to the intensity or extent of the expected outcome (e.g., "How much pain do you think you will experience after the treatment?"), while the *strength of the expectancy* refers to the subjective probability that a change will occur (e.g., "How likely is it that the response will occur?") (Kirsch, 2018, p. 6). Although these dimensions are distinctly defined, they are often confounded in research (Kirsch & Weixel, 1988; Lynn et al., 2023; Lunde et al., 2023) and rarely assessed simultaneously. To address this, Kirsch (2018) and Lunde et al. (2023) strongly recommended assessing and manipulating both dimensions in the same study for a deeper conceptual understanding. Moreover, Kirsch (1985, 2018) suggested that response expectancies are dynamic and can change in response to new information, highlighting the importance of measuring them multiple times within the same study. However, only very few empirical studies have followed this approach, making it a priority for future research.

Furthermore, the vast majority of studies have measured response expectancies using a single item, either in general terms related to emotional response ("How much positive mood do you expect to feel during this time?" Cristea et al., 2011) or in specific terms ("How anxious do you think you will feel right before the exam?", David et al., 2006). While these measures are consistent with published methodology (e.g., Montgomery & Bovbjerg, 2001; Montgomery et al., 1998; Montgomery & Bovbjerg, 2000) and are valid for unidimensional constructs (Allen et al., 2022; Ang & Eisend, 2018; Fuchs & Diamantopoulos, 2009), the necessity to measure this construct with multiple items remains a prior recommendation (Kirsch, 2018). This comprehensive approach to measurement will provide a more accurate and nuanced understanding of response expectancies and their influence on positive emotional outcomes.

The *fourth* notable limitation is the reliance on self-report measures for evaluating individuals' emotional experiences in relation to response expectancies. While self-report measures are valuable for accessing individuals' subjective experiences and perceptions of their emotions in the context of expectancy mechanisms, they may not always capture the full breadth of an individual's emotional state. Some individuals may lack the introspective ability to report their momentary experiences accurately or may provide responses skewed toward a desirable light. To overcome this limitation, a comprehensive assessment of emotional experiences induced by expectancy processes should incorporate a variety of measures. According to Mauss and Robinson (2010), integrating subjective assessments with physiological and behavioral data provides a more accurate and reliable perspective of emotional experiences.

Notably, the investigation of response expectancy in the context of positive emotions needs to be addressed using positive mood induction methods with high ecological validity and interventions that can be easily integrated into real-life contexts. High ecological validity ensures the findings are applicable and relevant to everyday life, making the results more generalizable beyond the laboratory setting. This approach would provide a more accurate representation of how response expectancies influence positive emotions in daily life.

Concluding remarks and relevance of present research

According to Response Expectancy Theory (Kirsch, 1985), response expectancies directly influence non-volitional outcomes, function independently of other psychological variables, and are self-reinforcing. Research exploring the role of response expectancies in the production of emotional outcomes has demonstrated that these expectancies are accurate, as evidenced by the significant correlation between expectancies and emotional experiences (e.g., Dilorenzo et al., 2011; Montgomery et al., 2007; Cristea et al., 2011). However, a significant limitation in the literature on response expectancy and emotional outcomes is the disproportionate number of studies investigating this relationship. While numerous studies have examined the relationship between response expectancy and negative emotions, only a few have explored this relationship in the context of positive emotions (Cotet & David, 2016). Furthermore, studies that focus on positive emotional outcomes rarely utilize experimental designs, and they have yet to incorporate a longitudinal approach to examine these effects over time. This disparity in the research underlines a critical gap in our understanding of how response expectancies can shape positive emotional experiences. This gap has significant implications for theoretical knowledge and practical applications, especially in therapeutic and intervention contexts where fostering positive emotions can be as crucial as mitigating negative ones (Pavic et al., 2022; McManus et al., 2018). Thus, studying the impact of response expectancies on positive emotions could lead to more comprehensive models of emotional regulation and inform practices that promote psychological well-being. By acknowledging and addressing this imbalance in research, the field can move toward a more holistic approach to understanding human emotions, paving the way for interventions that enhance positive emotional experiences and improve overall mental health.

Regarding the response expectancy construct, some emphasis and clarifications are necessary. Kirsch (1985) proposed that response expectancy can be understood in terms of two distinct dimensions: magnitude and strength. The strength dimension refers to the subjective probability of a given outcome occurring, specifically, how likely the expected result will happen. Conversely, the magnitude dimension concerns the intensity or size of the expected outcome, focusing on how substantial or impactful the anticipated outcome will be. Despite the clear distinctions between these dimensions, research often confounds them (Lynn et al., 2023; Lunde et al., 2023).

Furthermore, the research literature has predominantly focused on the magnitude of response expectancy, often neglecting the strength dimension. Additionally, these dimensions are rarely assessed simultaneously, which poses a significant limitation in fully capturing the nuances of response expectancy. Thus, there needs to be some clarity in understanding how each dimension independently affects psychological processes and outcomes. For example, it is crucial to distinguish whether a person's response is driven more by the intensity of the expected outcome or by the perceived probability of its occurrence, as each dimension has different implications for automatic responses and therapeutic intervention. Assessing both dimensions together would offer a more complete understanding of how expectancies affect emotional outcomes.

Another crucial aspect of the response expectancy construct is its dynamic nature. Kirsch (1985, 1990) underscored that response expectancies are not static; they can change over time in response to new experiences and are temporally sensitive. For instance, the accuracy of expectancies is higher when they are measured closer in time to the event. Recently, researchers in the field, including Kirsch (2018) and Lunde and collaborators (2023), have stressed the importance of measuring them multiple times within the same study. This approach enables researchers to capture the fluctuations in expectancies over time, providing valuable insights into the optimal timing and methods for adjusting interventions to enhance their therapeutic effects. This dynamic aspect needs to be addressed in the present thesis.

CHAPTER II. RESEARCH OBJECTIVES AND OVERALL METHODOLOGY

The present thesis focuses on addressing several objectives related to the concept of response expectancy (RE). Building on the theoretical and empirical frameworks laid out in Chapter I, the primary aim of this research was to investigate the relationship between RE for positive emotions and the actual experience of those emotions. To accomplish this, we focused on (1) positive emotions in general and (2) specific positive emotions, such as the state of relaxation. Beginning from this point, we initiated a series of studies addressing two key questions. The structure of these studies, aligned with the research objectives, is outlined in Figure 1.

The **first question** addresses the nature of the association between response expectancy and positive emotions: Are response expectancy and positive emotions significantly associated? If so, how does this relationship evolve, and do more generalized expectancies, such as optimism, play a role in this relationship? We formulated three specific objectives analysed in the first three studies to answer this question.

The **first objective** of our research was to investigate the relation between emotional predictions and positive emotions using a meta-analytic approach, building on the integrative model proposed by Coteț and David (2016). To achieve this, we conducted two meta-analyses: Study 1a examined the strength of the association between emotional predictions and positive emotions, while Study 1b assessed the magnitude of the difference between predicted and actual positive emotions. Through these analyses, we sought to provide a comprehensive understanding of how accurately individuals predict their positive emotional experiences and to what extent these predictions align with their actual emotions.

The **second objective** of our research was to extend the exploration of associations identified in the meta-analytic study by investigating the role of response expectancy as a mediator between generalized expectancies and positive emotions (Study 2). This investigation focused on two dimensions of response expectancy: the magnitude and strength of response expectancy. We decided to perform this analysis due to a noticeable gap in the existing literature, where the magnitude and strength of response expectancy dimensions are rarely examined concurrently in relation to emotional outcomes. By addressing this gap, we aim to provide a more comprehensive understanding of how these response expectancy dimensions are related to positive emotional experiences. Additionally, the experience of positive emotions was investigated at both subjective and physiological levels, contributing to a broader understanding of the relationship above using objective measures as well.

The **third objective** of our research was to study the associations between response expectancy for positive emotions and positive emotional outcomes using a longitudinal design (Study 3). Specifically, we tested whether response expectancy for positive emotions predicts subsequent positive emotions experienced in the short term (T0-T1, two weeks) and long term (T0-T2, four months). Most existing evidence on this association relies on correlational data obtained through cross-sectional designs. By employing a longitudinal approach, we aimed to provide more robust evidence regarding the predictive role of response expectancy in shaping positive emotional experiences, thus addressing a limitation in the current literature.

The **second question** in our research focuses on examining the impact of response expectancy on positive emotions: Does response expectancy significantly influence positive emotions, and under what conditions is this effect observable? To answer this question, we aimed to manipulate expectancies and observe their direct impact on emotional outcomes in the last two studies. Most of the existing evidence on the influence of response expectancy on non-volitional outcomes has been conducted within the context of placebo effect, where an inactive treatment or procedure is considered to elicit changes. Additionally, studies often focus on how response expectancy impacts negative emotions in the context of negative stimuli. Consequently, a significant gap exists in understanding how response expectancy impacts emotions in positive contexts. Thus, to answer this question, a fourth objective was formulated.

The **fourth objective** of our research was to manipulate response expectancies and examine their impact on emotional experiences through two distinct studies. In Study 4, we aimed to conduct an experimental study to investigate the effect of response expectancies on positive emotions, both in general and specifically on relaxation states, using a positive technique such as the "Safe Place" imagery. This intervention was administered in a single session within a controlled laboratory setting. The aim was to observe the immediate effects of manipulated expectancies on participants' emotional states in a highly controlled environment. Also, in Study 5, we extended our investigation to a more naturalistic setting by conducting a randomized controlled trial (RCT) to examine the effect of response expectancies on emotions within a positive intervention framework, such as gratitude intervention. This intervention was delivered over seven consecutive days in an ecological context, allowing us to assess the sustained impact of expectancy manipulations on emotional outcomes over a more extender period and in participants' everyday environments.

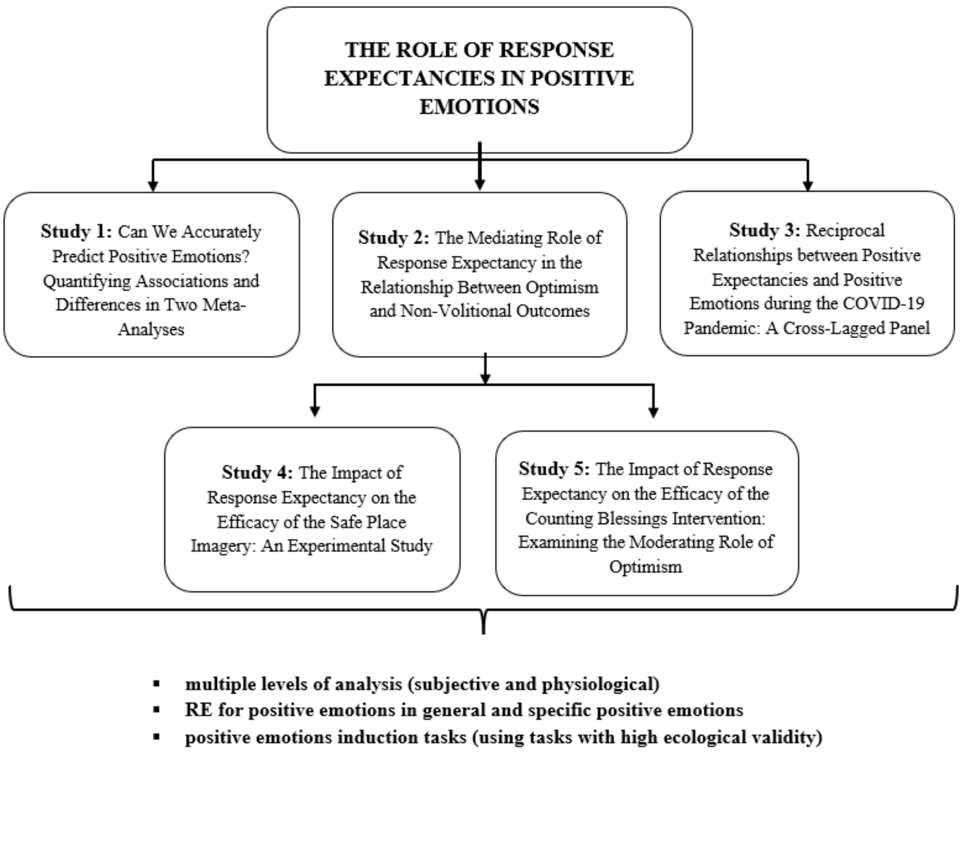

Figure 1. Schematic Overview of the Ph.D. Project Structure

CHAPTER III. ORIGINAL RESEARCH

Study 1: Can We Accurately Predict Positive Emotions? Quantifying Associations and Differences in Two Meta-Analyses

Introduction

The anticipation and subsequent experience of emotions in various contexts have been extensively investigated. Specifically, numerous studies showed that individuals predictions about the experience of specific emotions (e.g., anxiety, sadness, happiness, positive mood) have an impact on the experience of these emotions (e.g., Carlson et al., 2023; Cristea et al., 2011, Bauer et al., 2022).

The significance of this subject is well-established, emphasizing its impact on decision-making, emotional regulation in everyday life, and future planning (Carlson et al., 2023; Ferrer et al., 2015; Szpunar et al., 2014; Levine et al., 2018; Halpern et al., 2008).

Two methodological approaches, rooted in different theoretical frameworks, seek to elucidate the nature of the relationship between emotional predictions and subsequent emotional responses. According to response expectancy theory (Kirsch, 1985, 1990), there is a causal link between one's expectations and the non-volitional reactions in a specific situation. This relationship has been empirically demonstrated and quantified through correlations. According to this theory, predictions regarding future non-volitional and emotional responses are deemed accurate (e.g., Cristea et al., 2011; Dilorenzo et al., 2011; Podină & Vîslă, 2014; Vîslă et al., 2013). For instance, expecting to feel relaxed during a holiday typically results in experiencing this emotion automatically. Conversely, anticipating social anxiety during a job interview can lead to experiencing corresponding reactions.

In contrast, the affective forecasting approach (Gilbert et al., 1998; Gilbert & Wilson, 2007, 2009) emphasizes the discrepancies between emotional predictions and actual emotional responses during various life events. According to this approach, individuals often inaccurately predict their emotional reactions to specific situations (e.g., Carlson et al., 2023; Moeck et al., 2022; Levine et al., 2012; Hughes et al., 2022; Dunn et al., 2007; Buechel et al., 2014). For example, individuals might expect more intense happiness following a positive event, such as their preferred candidate winning a presidential election, than they experienced immediately after the event. Conversely, individuals experienced less intense disappointment after a negative event, such as failing a driving examination, than they had predicted.

Coteț and David (2016) proposed an integrative model in which affective forecasting is a subcategory of response expectancy. Within this framework, they supported two types of accuracy. Firstly, response expectancy theory considers accuracy in a relative sense, suggesting that emotions are partially controllable and experienced based on their anticipation. Secondly, the affective forecasting approach demonstrates inaccuracy in an absolute sense, indicating that emotions are often underpredicted or overpredicted. Coteț and David (2016) found in their meta-analysis a medium to large effect size for the correlation between predictions and emotions, and a small to medium effect size for the differences between predictions and actual emotions. Notably, their analysis included studies specifically focused on predicting positive emotions. Furthermore, previous meta-analyses by Levine et al. (2012) and Mathieu & Gosling (2012) assessed an overall effect size for emotional outcomes, including negative and positive emotions. Recognizing this gap in the literature and the need to understand better the specific mechanisms that drive the experience of positive emotions, we propose to conduct the first meta-analysis dedicated exclusively to positive emotional outcomes.

Additionally, current research suggests that moderating factors might influence the relationship between emotional predictions and actual experiences. Exploring these effects is critical as it can elucidate under what conditions emotional predictions are more or less accurate. Understanding these moderators is essential to refining our approaches to predicting and managing emotions effectively. Accumulated research on affective forecasting suggests that emotional accuracy can be influenced by the perceived importance of focal events for personal goals (e.g., Hoerger & Quirk, 2010; Hong et al., 2016; Verner-Filion et al., 2012). In this context, we propose exploring the impact of events with low and high personal relevance on emotional accuracy. Cristophe and Hansenne (2021) highlighted a methodological issue in affective forecasting research: participants are often required to predict their emotional response to a focal event, either in general or specific terms, but later report their actual experiences with varying degrees of specificity. This inconsistency in the measures used for predictions and reported experiences can lead to confusion. Building on these findings, we propose introducing the specificity of questions used to measure emotional predictions about a focal event as a potential moderator that could impact emotional accuracy. We also aim to replicate the importance of question specificity for reported experiences, operationalizing these constructs in terms of the frame for reference for predictions and emotional experiences. More than these, research on affective forecasting indicates that people's forecasting accuracy is influenced by the temporal distance between the prediction and the reported experience (Glenn et al., 2019; Aitken et al., 2021; Lench et al., 2019). Similarly, research within the response expectancy framework suggests that emotional accuracy is influenced by temporal distance, with closer distances between prediction and the target event typically being more accurate (e.g., Kirsch, 1985, 1990). Considering these results, we propose examining temporal distance as a moderator on two dimensions: the period between when the prediction was made and when the event occurred, and between when the event occurred and when the emotional experience was reported.

Based on the circumplex model proposed by Russell (Russell et al., 1980; Yuan et al., 2023), we categorized specific positive emotions according to their level of arousal (low, medium, or high), as specified in the literature. We propose to explore whether emotional accuracy is influenced by the varying levels of arousal characterizing positive emotional experiences. Recent research in response expectancy and affective forecasting suggests that age can influence emotional accuracy (e.g., Barber et al., 2023). We operationalized this moderator as both categorical (population type) and continuous (mean age) variables. Finally, we propose an exploratory moderator to test whether varying levels of individualism impact emotional accuracy, drawing on accumulated research highlighting cultural differences' relevance in influencing psychological constructs (Lim, 2016; Safdar et al., 2009).

General objectives

This meta-analysis examines the relationship between emotional predictions and positive emotions as outcomes. Drawing on the theoretical framework introduced by Coteț and David (2016), our research investigates two main aspects: the strength of the association between emotional predictions and positive emotions and the magnitude of difference between them.

Searching Strategy

We carried out a thorough literature search to identify studies that might be relevant to our research, using databases including PsycINFO, PubMed, SCOPUS, Web of Science, and ProQuest Central. This search was up to date as of 10 April 2024.

Inclusion Criteria

To be included in the meta-analysis, studies were required to meet the following criteria: (a) the study focused on predictions (as expectancies or forecasts) about future emotional responses; (b) the study measured both anticipated (t0) and actual (t1) emotional responses; (c) the study provided data that allowed for the calculation of effect sizes concerning the relationship between predicted and experienced emotions, either as correlations or as differences in means (d) the study was not a case study; (e) the study was published in English; and (f) the study appeared in a peer-reviewed journal.

Study Selection

Our search strategy identified 2,388 potentially relevant articles. After duplicate removal, 1,568 articles were reviewed for relevance based on their abstracts. Of these, 126 full-text articles were further evaluated for eligibility. We ultimately included 64 articles, encompassing 89 studies that satisfied our inclusion criteria for both Study 1 and Study 2. For Study 1, we selected 19 studies from 14 articles investigating the relationship between predictions and emotions, specifically reporting a correlation between these two variables. For Study 2, we included 50 articles incorporating 70 studies, resulting in 222 effect sizes. The PRISMA diagram (Moher et al., 2009) is illustrated in Figure 1.

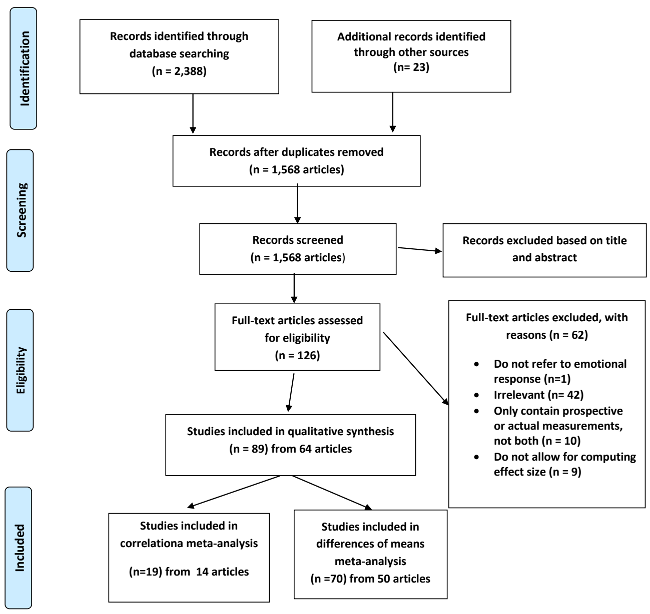

Figure 1: PRISMA Flow Chart

Data extraction

For each study included, we collected the following coded information: study identification data (authors, publication year), positive emotional outcome, and the data necessary for calculating effect sizes, along with a series of moderator variables. Additionally, we extended the category of positive outcomes addressed in previous meta-analyses (Coteț & David, 2016) by including specific emotions such as contentment, fascination, interest, and curiosity.

This initial meta-analysis focuses exclusively on the relationship between emotional predictions and positive emotions as outcomes. In this context, based on the theoretical model proposed by Coteț and David (2016), we examined (1) the association between predictions and positive emotions and (2) the difference between predictions and positive emotions using two distinct research methodologies. Although the distinction is purely methodological, we carried out a single literature search and selection process. Following this, we assigned each qualifying article to one or both of the meta-analytic studies. The methodologies for the two studies are similar, with specific distinctions noted where applicable. All the extracted data were uploaded into Comprehensive Meta-Analysis (CMA, Version 3:0; Brüggemann & Rajguru, 2022) for analysis.

Theoretical moderators

We investigated a series of theoretical and exploratory moderators to better understand the relationship between predictions and positive emotions. In this context, we replicated some existing moderators and proposed new ones based on the accumulated literature. For the replicated moderators, we only mention them here while their complex operationalization is detailed in previous meta-analyses (Coteț & David, 2016; Mathieu & Gosling, 2012). These include the specificity of the emotional response (affect or mood), the valence of the event (positive, negative, or unknown), familiarity with the event (familiar, unfamiliar, or unknown), and the research area to which the article belongs (response expectancy or affective forecasting).

We proposed several new moderators, defined a priori, including the relevance of the event (high personal relevance vs. low personal relevance), the frame of reference for prediction (general vs. specific), and the frame of reference for emotional experience (general vs. specific). Additionally, we consider the temporal distance between prediction and the focal event (short vs. average vs. long vs. unspecified), the temporal distance between the focal event and emotional experience (short vs. average vs. long vs. unspecified), the level of emotional activation (low vs. medium vs. high vs. unspecified), country, and type of population. Regarding the relevance of an event, we coded as "high personal relevance" any event that holds personal significance or importance (e.g., receiving an "exam grade" or learning the "results of the presidential election," which we interpreted as events with relevant and significant personal impact). Conversely, we coded as "low personal relevance" any event with little or no personal significance (e.g., "exploring an art gallery" or "winning at a gamble"), typically tasks assigned by experimenters during experimental studies. Regarding the frame of reference for prediction, we categorized as "general" those situations where questions used to measure emotional predictions after the focal event were formulated in broad terms (e.g., "In general, how happy will you feel a week after the game if your favorite team loses?"). We coded as "specific" those questions that explicitly link emotions to particular details of the focal event (e.g., "During the week after you find out your grade, how happy will you feel about your grade?" in Levine et al., 2012). Regarding the frame of reference for experience, we coded the situation as "general" when the questions used to measure emotions after the focal event did not specifically refer to it (e.g., "In general, how happy are you feeling these days?" in Tomlinson et al., 2010). We coded as "specific" the situation where the question explicitly referenced the target emotion about to the focal event (e.g., " How happy will you feel about the candidate you support being elected President?" in Levine et al., 2012, a question where both the focal event and the target emotion are clearly mentioned). We coded the temporal distance between the prediction and the focal event as "short time" when the emotional prediction was made immediately or on the same day before the focal event. We coded the situation as "average time," in which the emotional prediction was made two days to one month before the focal event. We considered "long time" the scenario in which the emotional prediction was made more than a month before the focal event. Finally, we coded it as "unspecific" in cases where the time between the emotional prediction and the focal event was not mentioned or could not be inferred from the context. Regarding the temporal distance between the focal event and the emotional experience, we coded it as "short time" when the distance between the focal event and the reporting of the emotional experience was immediate or on the same day as the focal event. We coded as "average time" those instances where the emotional experience was reported from two days to one month after the focal event. We classified it as a "long time" when the emotional experience was reported more than one month after the focal event. Finally, we coded it as "unspecific" when the distance between the focal event and the reporting of the emotional experience was not mentioned or could not be inferred from the context. Regarding the level of emotional activation, we coded as "low" those emotions with a low arousal level, such as relaxation or contentment. We coded as "medium" emotions with a moderate arousal level, such as happiness or enjoyment. We coded as "high" those emotions with a high arousal level, such as excitement or interest. Conversely, we coded as "unspecific" those situations in which positive emotions were addressed in general terms or were presented with a total score encompassing more specific emotions characterized by varying arousal levels. Regarding the country moderator, we coded studies conducted in the United States as "United States" and those conducted in various European countries as "Europe." We coded as "Other" those studies conducted in countries with fewer represented studies, such as Canada or Australia. Regarding the type of population, we categorized the samples used in the studies into three groups based on their specifications: "children and adolescents," "students," and "adults." As continuous moderators, we included individualism scores for the countries where the studies were conducted, participants' mean age, and the percentage of female participants. Regarding individualism, we incorporated the cultural dimension using specific scores for each country based on established metrics developed by Geert Hofstede and subsequently updated (Minkov & Kaasa, 2022; Hofstede, 1991) (link: https://www.hofstede-insights.com/country-comparison-tool), as well as those proposed by Welzel (Beugelsdijk & Welzel, 2018; Welzel, 2013).

Study 1a : The association between emotional predictions and positive emotions

The primary goal of this study was to quantify the relationship between predictions and positive emotions. In this sense, we proposed to a) calculate the overall effect size of this relationship, b) determine the effect size for specific outcomes, and c) examine potential moderators that might influence the strength of this association.

Procedure

All Pearson's r-effect sizes were reported, and when unavailable, they were computed using either existing data or the sample size. Outcomes from the same study were reported separately, and different time points were also noted where necessary. An average effect size for each study was reported, combining multiple outcomes if the study included several. A higher correlation coefficient (r) indicates a stronger relationship between expectations and feelings. According to accepted standards, a range of 0.1 to 0.3 indicates a small effect size, while a range of 0.3 to 0.5 indicates a moderate effect size and a value of 0.5 or higher represents a large effect size (Cohen, 1988).

Characteristics of included studies

The final sample comprised 19 studies from 14 articles, yielding 27 effect sizes. This discrepancy resulted from several articles encompassing multiple relevant studies. The combined sample size for these articles was 2,846, with individual studies having sample sizes between 20 and 430. The mean age was 25.34, with a range of mean ages from 18.60 to 60. 62.06% of the participants were women, ranging from 4.5% to 84.70%. In most studies (18 out of 19), participants were drawn from a convenience sample.

Results

For the first objective, we computed the average correlation between emotional predictions and positive emotional outcomes, which yielded a medium to large and significant overall effect size, with r = 0.45, 95% CI [0.34, 0.54], p < 0.001.

A random effects model was employed to conduct the overall test of heterogeneity, which indicated significant heterogeneity, Q (18) = 202.09, p < 0.001. The percentage of heterogeneity among studies not attributable to sampling error was estimated at 91%, indicating a high level of heterogeneity (Higgins et al., 2003). The effect sizes for individual outcomes were significant across all positive emotions, ranging from 0.20 to 0.59. Specific details about the effect sizes for each outcome are presented in Table 1.

Table 1. Effect Sizes for Specific Positive Emotional Outcomes in *Study 1a*.

Outcome	***k***	***N***	***r***	***95% CI***	***I2***
Positive emotions (overall)	19	2846	0.45	[0.34; 0.54]	91%
Positive emotions after removing outliers	15	1832	0.39	[0.30; 0.48]	76%
Positive affect	3	221	0.40	[0.27; 0.51]	0%
Positive mood	6	644	0.56	[0.40; 0.68]	85%
Happiness	7	1170	0.35	[0.009; 0.96]	94%
Pleasure	2	511	0.59	[0.53; 0.64]	0 %
Excitement	1	189	0.20	[0.06; 0.034]	0 %

Moderation analysis

For the secondary objective, a series of theoretical and exploratory analyses of moderators was conducted to determine if any candidate could explain the high heterogeneity in the data. For categorical moderators, variables were analysed using a mixed-effects meta-analytic categorical test. In this framework, studies within each subgroup are pooled using the random-effects model, whereas tests to identify significant differences across subgroups are performed using a fixed-effects model. Three of the tested moderators emerged as significant. Specific effect sizes and *I*2 index of heterogeneity for all moderators are reported in Table 2.

Table 2. Effect sizes for categorial moderators in *Study 1a*.

Categorial Moderators	**Category**	***k***	***r***	***CI***	**I2**	***p***
Specificity of emotional response	Mood	12	0.41	[0.25; 0.54]	94%	0.230
	Affect	7	0.52	[0.40; 0.63]	73%	
Valence of event	Positive	7	0.47	[0.28; 0.62]	83%	0.002*
	Negative	2	0.22	[0.10; 0.33]	0 %	
	Unknown	9	0.51	[0.38; 0.62]	90%	
Familiarity with the event	Familiar	2	0.37	[0.27; 0.46]	3%	0.499
	Unfamiliar	3	0.42	[-0.03; 0.73]	96%	
	Unknown	14	0.46	[0.33; 0.57]	90%	
Relevance of event	Relevant	11	0.41	[0.23; 0.55]	94%	0.302
	Unknown	8	0.51	[0.39; 0.61]	73%	
Frame of reference for prediction	Specific	13	0.51	[0.38; 0.61]	92%	0.009*
	General	6	0.30	[0.19; 0.39]	43%	
Frame of reference for experience	Specific	11	0.53	[0.43; 0.62]	83%	< 0.001***
	General	7	0.23	[0.14; 0.32]	35 %	
Temporal distance between prediction and focal event	Short time	7	0.54	[0.44; 0.63]	70%	0.085
	Average time	12	0.39	[0.22; 0.53]	93%	
Temporal distance between focal event and reported experience	Short time	9	0.55	[0.46; 0.64]	77%	0.052
	Average time	6	0.34	[0.6; 0.56]	96%	
	Long time	3	0.33	[0.12; 0.52]	75%	
Emotional arousal	High	NA	NA	NA	NA	0.311
	Medium	9	0.41	[0.22; 0.56]	94%	
	Unspecific/mixed	9	0.51	[0.38; 0.62]	83%	
Clinical Status	Non-clinical condition	18	NA	NA	NA	NA

	Clinical condition	1	NA	NA	NA	
Line of research	Affective forecasting	18	NA	NA	NA	NA
	Response expectancy	1	NA	NA	NA	
Country	United States	10	0.49	[0.36; 0.61]	90%	0.322
	Europe	9	0.39	[0.19; 0.55]	91%	
Population	Students	14	0.48	[0.37; 0.58]	86%	0.668
	Adults	4	0.41	[0.009; 0.66]	95%	

Note: ⁎ p < .05; ⁎⁎ p < .01 and ⁎⁎⁎ p < .001; NA – not applicable

For continuous moderators, we conducted meta-regression analyses using an unrestricted maximum likelihood model alongside the Knapp-Hartung method (Borenstein et al., 2009). Regarding continuous moderators, the percentage of female participants emerged as a significant moderator, as detailed in Table 3.

Table 3. Effect sizes for continuous moderators in *Study 1a*.

Continuous Moderator	***β***	***SE***	***LL***	***UL***	***p***
Individualism according Welzel	-0.002	0.005	-.001	0.007	0.581
Individualism according Hofstede	-.002	0.004	-.001	0.006	0.559
Publication year	0.001	0.009	-.001	0.03	0.071
Mean Age	-0.01	0.005	-0.02	0.0002	0.055
Female	0.005	0.002	0.0007	0.01	0.025*

Note: ⁎ p < .05.

Discussion

This study focused on quantifying the association between emotional predictions and the experience of positive emotions. Our findings indicate a medium to large and significant effect size for this association, aligning with earlier meta-analysis (Coteţ & David, 2016; Mathieu & Gosling, 2012). In other words, predictions reliably indicate both the direction and the relative intensity of the emotions that individuals will experience in a given situation, demonstrating their accuracy in a relative sense. Furthermore, our results align with findings from other research areas that quantified the association between predictions and non-volitional outcomes, specifically related to cancer treatments (Sohl et al., 2009; Devlin et al., 2017; Fletcher et al., 2018).

Unlike the meta-analysis conducted by Coteț and David (2016), which found no significant moderators, our study identified four moderators affecting the association between predictions and positive emotions. These include the valence of the event, the frame of reference for prediction, the frame of reference for experience, and the percentage of females included in the studies. The temporal distance between the focal event and the reported experience also emerged as a marginally significant moderator. The valence of the event moderated the association between predictions and positive emotions. The association was stronger in the case of events with positive valence, supporting the accuracy in a relative sense. However, half of the studies in this meta-analysis (k = 9) fell into a residual category consisting of events with unknown valence. This category includes studies that either combined negative and positive events or involved events that could alternatively be classified as neutral. In contrast, some studies (k = 7) were conducted in relation to an event with positive valence, and only two studies were allocated to a negative event. Before drawing any firm conclusions, more studies concerning events with clearly defined positive or negative valence are needed. It is clear that when the valence of an event is unknown, the accuracy of emotional predictions cannot solely be ascribed to the event's neutrality but to its ambiguous valence. Regarding the frame of reference for prediction, our results indicated that individuals are more accurate in predicting emotions related to a specific event than in predicting their general emotional responses. People were also more accurate when asked to rate their emotions in relation to a particular event rather than when asked to report their emotions in general without being prompted about a specific event. This finding aligns with prior research (e.g., Levine et al., 2012; Moeck et al., 2022), suggesting that emotional accuracy increases with the questions' specificity. Regarding demographic moderators, only gender seems to influence emotional accuracy. Specifically, including women in studies tends to increase emotional accuracy, supporting that women generally exhibit greater emotional intelligence, particularly in their ability to identify and express emotions. Finally, the temporal distance between the focal event and the reported experience emerged as a marginally significant moderator. The accuracy tends to be stronger when emotions are measured immediately after the focal event or closer to it and decreases over time. These results follow the response expectancy theory (Kirsch, 1985, 1990; Cristea et al., 2011; David et al., 2006; Cimpean & David, 2019; Montgomery et al., 2007).

Study 1b: The differences between emotional predictions and positive emotions

The primary goal of the present study was to measure the extent of difference between predictions and positive emotions. To achieve this, we aimed to a) calculate the overall effect size for this difference, b) estimate the effect size for individual outcomes, and c) examine potential moderators that could influence this relationship.

Procedure

We calculated Hedges' g effect sizes wherever sufficient data were available. Each study's outcome was reported separately, including different time points where applicable. Furthermore, we treated each study as a distinctive unit of analysis. According to established conventions, an effect size value was considered small (ranging from 0.2 to 0.5), moderate (ranging from 0.5 to 0.8), and large (0.8 or higher) (Borenstein et al., 2009).

Characteristics of included studies

The final sample comprised 82 studies from 50 articles, resulting in 195 effect sizes. This variation was due to some articles containing multiple relevant studies. The cumulative sample size across these studies was 17.611, with individual study sample sizes ranging from 5 to 727. The mean age of participants was 24.78, with mean ages varying from 5.50 to 87. The female participants accounted for around 61.71% of the total, with separate research reporting female participation rates ranging from 31.28% to 100%. The majority of studies used convenience samples (78 out of 82).

Results

First, we calculated the difference between emotional predictions and positive emotional outcomes. This analysis revealed a small and significant overall effect size, where $g = 0.18$, 95% CI [0.10; 0.27], $p < 0.001$.

A random effects model was used to perform the overall heterogeneity test, revealing significant heterogeneity, $Q(90) = 1430.73$, $p < 0.001$. The proportion of heterogeneity not attributed to sampling error was estimated at 94%, suggesting a high level of heterogeneity (Higgins et al., 2003). The effect sizes for each specific outcome ranged from -0.66 to 0.90. Table 4 includes the effect sizes for each particular positive emotion.

Table 4. Effect Sizes for Specific Positive Emotional Outcomes in *Study 1b.*

Outcome	***k***	***g***	***95% CI***	***I2***
Positive emotion (overall)	91	0.18	[0.10; 0,27]	94%
Positive emotions after removing outliers	56	0.21	[0.16; 0.26]	57%
Positive affect	19	0.01	[-0.17; 0.20]	88%
Positive mood	18	0.18	[0.08; 0.28]	87%
Happiness	46	0.27	[0.16; 0.38]	92%
Pleasure	4	0.31	[-0.41, 1.04]	98%
Contentment	1	0.001	[-0.27; 0.22]	0%
Enjoyment	3	-0.66	[-.088; -0.47]	0%
Fascination, interest, curiosity	1	0.15	[-0.16; 0.47]	0
Rejoicing	1	0.90	[0.43; 1.37]	0
Relaxation	1	0.11	[-0.21; 0.42]	0%

Moderation analysis

Second, we conducted a range of theoretical and exploratory analyses on potential moderators to investigate the sources of heterogeneity observed in the data. We analyzed categorical moderators using a mixed-effects meta-analytic categorical test. In this approach, studies within each subgroup were combined using a random-effects model, while significant differences between subgroups were assessed using a fixed-effects model. Seven moderators emerged as significant. Detailed effect sizes and the I2 index of heterogeneity for all categorial moderators are noted in Table 5.

Table 5. Effect sizes for categorial moderators in *Study 1b*.

Categorial Moderators	Category	*k*	*g*	*CI*	*I2*	*p*
Specificity of emotional response	Mood	39	0.31	[0.20; 0.41]	93%	0.010**
	Affect	52	0.07	[-0.06; 0.22]	94%	
Valence of event	Positive	29	0.13	[-0.05; 0.32]	95%	0.018*
	Negative	11	0.25	[0.12; 0.38]	76%	
	Unknown	22	-0.05	[-0.22; 0.10]	91%	
Familiarity with the event	Familiar	16	0.32	[0.14; 0.49]	88%	0.010**
	Unfamiliar	16	0.38	[0.20; 0.55]	93%	
	Unknown	54	0.08	[-0.03; 0.20]	94%	
Relevance of event	Relevant	40	0.31	[0.20; 0.41]	92%	0.017*
	Unknown	45	0.09	[-0.05; 0.23]	94%	
Frame of reference for prediction	Specific	61	0.13	[0.01, 0.24]	94%	0.062
	General	29	0.29	[0.16; 0.42]	93%	
Frame of reference for experience	Specific	64	0.10	[-0.009, 0.21]	94%	0.004**
	General	26	0.36	[0.22; 0.49]	93%	
Temporal distance between prediction and focal event	Short time	44	0.08	[-0.08; 0.24]	95%	0.056
	Average time	32	0.22	[0.11; 0.33]	93%	
	Long time	8	0.34	[0.23; 0.45]	33%	
	Unspecific	6	0.33	[0.08; 0.67]	92%	
Temporal distance between focal event and reported experience	Short time	51	0.06	[-0.07; 0.20]	94%	0.040*
	Average time	27	0.30	[0.17; 0.43]	92%	
	Long time	5	0.38	[0.08; 0.68]	92%	
	Unspecific	6	0.37	[0.08; 0.67]	92%	
Emotional arousal	High	NA	NA	NA	NA	0.241
	Medium	53	0.22	[0.09; 0.34]	95%	
	Low	NA	NA	NA	NA	
	unspecific or mixed	35	0.12	[0.03; 0.22]	87%	
Country	United States	59	0.26	[0.15; 0.36]	95%	0.003**
	Europe	16	0.16	[-0.03; 0.36]	88%	
	Other	16	-0.10	[-0.27; 0.08]	86%	
Population	Children and Adolescents	2	0.27	[0.02; 0.52]	0	0.672
	Students	62	0.19	[0.09; 0.30]	94%	
	Adults	25	0.14	[-0.01; 0.30]	92%	

Note: $*$ p < .05; $**$ p < .01; NA – not applicable

For continuous moderators, we conducted meta-regression analyses using an unrestricted maximum likelihood model (Borenstein et al., 2009). Among these moderators, the publication year, mean age, and the percentage of female participants were found to be significant, as illustrated in Table 6.

Table 6. Effect sizes for continuous moderators in *Study 1b*.

Continuous Moderator	*β*	*SE*	*LL*	*UL*	*p*
Individualism according Welzel	-0.006	0.006	-0.001	0.007	0.361
Individualism according Hofstede	-0.005	0.004	-0.01	0.003	0.201
Publication year	-0.01	0.006	-0.02	-0.0007	0.038*
Mean Age	-0.008	0.003	-0.01	-0.001	0.012*
Female	-0.01	0.005	-0.02	-0.002	0.012*

Note: $*$ p < .05.

Discussion

This study aimed to quantify the mean difference between emotional predictions and the experience of positive emotions. Our findings revealed a small but significant effect size for this difference (g = 0.18). This indicates that while individuals sometimes inaccurately predict positive emotions, the discrepancies are not extensive, suggesting a general alignment between expected and experienced emotions. Similarly, the effect size (d = 0.31) reported by Coteț and David (2016) falls within the small to moderate range, specifically in the context of positive emotions. In contrast, the moderate effect size (g = 0.55) reported by Levine and colleagues (2012) for overall emotions— including positive and negative emotions—suggests that emotional predictions may be less accurate across a broader spectrum of emotional states. This larger effect size indicates that discrepancies between predicted and experienced emotions become more pronounced when negative emotions are considered.

Some of the tested moderators were significant. These results imply that the inaccuracy between predictions and emotions varies depending on some factors. The following moderators were imposed as significant for the difference between prediction and emotions: specificity of emotional response, frame of reference for experience, relevance of the event, temporal distance between the focal event and reported experience, and valence of event and country. Regarding the specificity of emotional responses, the results indicated that predictions are more inaccurate for general emotions, such as mood, compared to more specific emotions, such as affect. This finding is consistent with previous research (e.g., Mathieu & Gosling, 2012; Lench et al., 2019), which has also shown that the level of specificity in emotional experiences affects the accuracy of emotional predictions. Additionally, the frame of reference for the experience played a moderating role in the magnitude of the inaccuracy between predictions and positive emotions. Specifically, when individuals focused on a particular event and its detailed aspects, the accuracy of their emotional predictions improved. The detailed specificity prompted by the focal event helped reduce emotional inaccuracy, suggesting that having a more concrete and specific context can lead to better emotional forecasting. Our result aligns with a recent study by Barber et al. (2023) which found that individuals were more accurate in predicting their feelings about a specific event than their general emotional state. Concerning the relevance of events, our results indicated that the discrepancy between predictions and emotions becomes more pronounced for events with high relevance and perceived importance compared to events with low personal relevance. These findings suggest that the accuracy of emotional predictions is negatively influenced by the subjective importance and personal relevance that individuals attribute to different events. Our results align with previous studies that indicated the accuracy of emotional predictions can be influenced by the perceived value of personal goals (e.g., Hong et al., 2016; Hoerger & Quirk, 2010; Hoerger, Quirk, Lucas, & Carr, 2010; Verner-Filion et al., 2012). Concerning the temporal distance between the focal event and the reported experience, our results indicated that as the time interval increases, the inaccuracy of emotional predictions also increases. Conversely, as the time interval decreases, the inaccuracy diminishes. This suggests that the closer the event is to the time of emotional reporting, the more accurate the emotional predictions are likely to be. This trend highlights the importance of temporal proximity in the accuracy of emotional forecasting, as previously documented (Levine et al., 2012; Finkenauer et al., 2007; Liberman et al., 2002; Lench et al., 2019. Thus, these findings point out that predicting errors are not constant; instead, they vary across dimensions of temporal distance. Additionally, in line with previous research (Coteț and David, 2016; Mathieu & Gosling, 2012; Finkenauer et al., 2007), our findings revealed that emotional predictions concerning events with negative valence are generally more inaccurate in absolute terms than predictions for events with positive valence. This suggests that individuals have greater difficulty accurately forecasting their emotional responses to negative events than to positive ones. This discrepancy may indicate that accurately predicting negative emotions is particularly difficult, perhaps because of their complex nature and the greater variation in how individuals experience and deal with unpleasant events. Regarding demographic moderators, our data show that the effect size for the difference between predictions and emotions diminishes with an increase in the average age of participants. This aligns with previous studies suggesting that individuals with a higher average age may have better emotional prediction accuracy (Barber et al., 2023; Nitzan et al., 2020). Additionally, an increased proportion of female participants in studies appears to reduce emotional inaccuracy.

General discussions

Building on the integrative model introduced by Coteț and David (2016), our study aimed to quantify both the association and the discrepancy between emotional predictions and the experience of positive emotions. To achieve this, we conducted two separate meta-analyses. The first analysis focused on the accuracy of intensity in the association between predicted and experienced emotions. The second analysis explored the magnitude of inaccuracies between these predictions and actual experiences. Our findings are consistent with previous research, indicating that predictions are generally accurate in a relative sense, as supported by response expectancy theory (Kirsch, 1985, 1990), with a medium to large effect size for this association (r = 0.45). However, when examining the accuracy of these predictions in absolute terms, our results show a small but statistically significant effect size for the discrepancies (g = 0.18), aligning with the affective forecasting framework (Gilbert & Wilson, 2007, 2009). In other words, individuals can predict the general direction and intensity of their emotional responses. However, the precision of these predictions is often less than perfect, highlighting a nuanced landscape of emotional predictions where expectations are relatively but not absolutely accurate.

Exploring the intensity of association and magnitude of difference between predictions and emotions, some moderators emerged as significant. The valence of the event, the frame of reference for experience, and the percentage of females moderated both relationships. Specifically, emotional accuracy is stronger when predicting positive emotions related to positive events (Study 1). Conversely, inaccuracy is more evident when predicting positive emotions in the context of negative events (Study 2). Furthermore, the association between predictions and positive emotions is stronger when reporting emotions about a specific focal event (Study 1). In contrast, the difference between predictions and emotions is more pronounced when reporting emotions in general terms (Study 2). Finally, the presence of females in the studies significantly influenced emotional accuracy in relative and absolute terms. Simultaneously, the results indicated that emotional arousal and individualism did not moderate the investigated relationships. Regarding the moderator role of emotional arousal, we coded four categories: "High," "Medium," "Low," and "Unspecific or mixed." Many studies reported positive affect or mood in general terms, while others indicated emotions with different arousal levels, which we categorized as "Unspecific or mixed." There were insufficient studies in the literature corresponding to positive emotions with low and high arousal levels. To address this gap, future studies must be explicitly conducted on positive emotions with low and high arousal levels before drawing definitive conclusions regarding emotional accuracy for emotions with different arousal levels. Regarding the individualism dimension, several possible explanations could account for the lack of a significant moderation effect. First, many of the studies included in the analysis sampled participants from cultures with similar levels of individualism, particularly those with medium to high levels. In contrast, studies conducted on samples with low individualism were underrepresented, resulting in low variability and making it difficult to detect a moderation effect. Second, emotional prediction processes might be more universal and less influenced by cultural dimensions like individualism, meaning people across different cultures could have similar patterns in predicting non-volitional reactions.

Study 2: The Mediating Role of Response Expectancy in the Relationship Between Optimism and Non-Volitional Outcomes Following VR-Induced Positive Mood

According to the Response Expectancy Theory proposed by Kirsch (1985), response expectancy represents anticipating a particular outcome or response that an individual expects in a specific context or situation. This theory posits that response expectancies (1) automatically determine non-volitional outcomes, (2) operate independently of other psychological mediators, and (3) have a self-confirming nature. Kirsch (1985) defined nonvolitional responses as those "experienced as occurring automatically, without volitional effort." Non-volitional outcomes encompass various emotional reactions (e.g., relaxation, distress) and other subjective states (e.g., pain and fatigue arising as side effects of chemotherapy). For example, when we expect to feel relaxation, our expectations enhance the probability of us experiencing such a state in a particular situation.

Kirsch (1985, 1990) proposed that response expectancy comprises strength and magnitude. The strength dimension refers to the subjective probability of an expected outcome occurring, while the magnitude dimension concerns the intensity or size of the expected result. Although these dimensions are clearly defined, they are often confounded in research (Kirsch & Weixel, 1988; Lynn et al., 2023; Lunde et al., 2023), with studies predominantly focusing on magnitude while frequently neglecting strength (Kirsch, 2018; Lunde et al., 2023). Moreover, these dimensions are rarely assessed simultaneously, which limits a comprehensive understanding of the term response expectancy (Kirsch, 2018). Clarifying whether a response is driven more by the expected outcome's intensity or perceived probability is crucial, as each dimension can have distinct implications for automatic responses and therapeutic interventions. Simultaneous assessment of both dimensions would offer a more comprehensive insight into how expectancies influence emotional outcomes, addressing a significant gap in the response expectancy construct with important theoretical and practical implications.

A review of research on response expectancy, which examines the influence of expectancies on emotional outcomes, emphasizes its important role in influencing both positive and negative emotions, mainly through the magnitude dimension of these expectancies (e.g., Cristea et al., 2011; David et al., 2006; DiLorenzo et al., 2011; Kirsch, 1997; Montgomery et al., 2007; Podină & Vîslă, 2014; Vîslă et al., 2013; Geers & Lassiter, 2002). For instance, the expectancy of anxiety before an exam has been shown to correlate positively with distress felt just before the test. In contrast, the expectancy for relaxation has been associated with experiencing a relaxation response during the event (David et al., 2006). Moreover, research consistently shows that response expectancies can accurately predict emotional outcomes in both cross-sectional and experimental studies (Cristea et al., 2011; Geers & Lassiter, 2002; Montgomery et al., 2007; Podina & Vîslă, 2014; Vîslă et al., 2013). Furthermore, a meta-analysis conducted by Coteţ and David (2016) identified moderate effect sizes for the associations between expectancies and both negative ($r = 0.46$) and positive emotions ($r = 0.39$), highlighting the significant influence of expectancies in shaping emotional outcomes.

Despite growing interest in the influence of response expectancy on emotional outcomes, notable gaps remain in empirical research. The literature reveals a significant imbalance, with numerous studies focusing on the impact of response expectancies on negative emotions, particularly in negative contexts. In contrast, the exploration of their effect on positive emotions remains limited (Cotet & David, 2016; Alexander et al., 2021).

Understanding the experience of positive emotions is equally significant to understanding and addressing negative emotions (Pavic et al., 2022). Both aspects contribute to a holistic comprehension of emotional well-being, informing strategies for enhancing positive affect and effectively managing negative affect in various contexts.

In addition, response expectancies, characterized as situation-specific anticipations, are associated not only with emotional outcomes but also with trait characteristics, such as an optimism-pessimism disposition (Montgomery et al., 2003; Sucala & Tatar, 2010). Specifically, researchers have suggested that response expectancies might represent one potential mechanism through which optimism-pessimism, as generalized expectancies, contributes to emotional experiences. Individuals high in pessimism (i.e., a negative outlook towards the future) might endorse high response expectancies for negative emotions (i.e., anticipations of experiencing negative emotions), which might further explain their experience of negative emotions. Conversely, individuals high in optimism (i.e., a positive outlook towards the future) also endorse high response expectancies for positive emotions (i.e., anticipations of experiencing positive emotions), which further explains their experience of positive emotions. However, despite these suggestions and some preliminary findings pointing towards these associations, to our knowledge, no study investigated the potential mediator role of response expectancies in the relationship between optimism-pessimism and the experience of positive emotional outcomes. Preliminary studies have suggested that response expectancy for negative emotions is negatively associated with optimism and positively associated with pessimism (e.g., Cristea et al., 2011; Dilorenzo et al., 2011; Montgomery & Bovbjerg, 2004; Podina & Vîslă, 2014), while response expectancy for relaxation is positively associated with optimism and negatively associated with pessimism (Dilorenzo et al., 2011).

Advancing our understanding of the mediators underlying the relationship between optimism-pessimism and emotional functioning could shed light on more proximal factors (e.g., specific expectancies) through which an optimistic mindset (i.e., generalized expectancies) impacts positive emotional functioning. Thus, building on established research suggesting that response expectancy might significantly mediate the relationship between optimism-pessimism and emotional functioning, we aimed to test this hypothesis by focusing on the positive emotional and physiological outcomes reported after employing a validated mood induction method. Specifically, we tested whether having a higher score on optimism is related to endorsing more response expectancies for positive emotions and relaxation (focusing concurrently on both dimensions of response expectancies: magnitude and strength), which further explain the experience of positive emotions and relaxation states during and after a positive mood induction procedure.

Research shows that Virtual Reality (VR) relaxation applications effectively induce relaxation and positive affective states on both subjective and objective measures, especially those immersing users in natural environments like beaches and forests with corresponding natural sounds (e.g., Adhyaru & Kemp, 2022; Anderson et al., 2017; Hedblom et al., 2019; Pallavicini et al., 2022; Pallavicini & Pepe, 2020; Riches et al., 2021, 2023). Thus, VR is efficient in emotion induction studies, offering the advantage of eliciting more realistic emotional responses while enabling better control over subjective, behavioral, and physiological reactions and amplifying the duration of induced emotions (Di Pompeo et al., 2023).

Objectives

Thus, the main objective of the present study was to investigate the relationships among optimism (predictor variable), response expectancy with its two dimensions (magnitude and strength as parallel mediators), and emotional and physiological outcomes (criterion variables) during a positive mood induction based on a VR session. Specifically, we aimed to explore how these psychological factors relate to states of relaxation (specific positive emotion), positive emotions, and physiological indices (e.g., Heart Rate (HR), Root Mean Square of Successive Differences (RMSSD), and Skin Conductance Level (SCL)). Also, we specifically tested several parallel mediation models to extend the understanding of how response expectancy dimensions mediate the relation between optimism and non-volitional outcomes.

In the first four mediation models, optimism was the predictor variable, while response expectancy for relaxation (both magnitude and strength dimensions) served as parallel mediators. The criterion variables were considered separately and included relaxation states, heart rate (HR), root mean square of successive differences (RMSSD), and skin conductance level (SCL). In the second set of four mediation models, response expectancy for positive emotions (both magnitude and strength dimensions) served as parallel mediators, with positive emotions, HR, RMSSD, and SCL treated as separate criterion variables. Given that the emotional responses of interest were specifically relaxation and, more generally, positive emotions, we followed Kirsch's (2018) recommendation to measure expectancies that parallel the targeted emotional response. Therefore, we introduced two categories for measuring expectancies: response expectancy for relaxation and response expectancies for positive emotions.

2. Methods

The protocol has been registered on the AsPredicted pre-registration platform under the number 117524 (link: https://aspredicted.org/XY9_VGR).

2.1. Participants

The initial sample consisted of 228 participants recruited through online postings on social University groups between December 2022 and April 2023. Inclusion criteria included (a) consent to participate in the study, (b) being at least 18 years old, and (c) the absence of the following conditions: a history of motion sickness, vertigo, migraine, and dizziness, as well as an epilepsy diagnostic. A number of 40 participants did not meet the inclusion criteria, while 61 participants withdrew from the study. Thus, the final sample comprised 137 participants, 97 females (70.8%) and 40 males (29.2%), with an age range of 18 to 50 years and a mean age of 21.99 (SD=4.69).

2.2. Measures

2.2.1. Predictor variable: *Optimism*

Optimism was measured using the Life Orientation Test-Revised (LOT-R; Scheier et al., 1994). The optimism and reversed pessimism scores were added to create the final score. Values range from 0 to 24, and higher scores indicate a more optimistic perspective. The LOT-R was a unidimensional construct (Cano-García et al., 2015). According to Hinz and collaborators (2021), the LOT-R proved to have good psychometric properties. The internal consistency of optimism in the current study was high (α =.858).

2.2.2. Mediator variables*: Response expectancy for positive emotions and Response expectancy for relaxation*

Participants' expectancies were evaluated based on two dimensions that compose the response expectancy construct: the expected magnitude and the strength of the expectancy, as previously described by Kirsch (1985, 1990). Following Krisch's (2018) recommendations regarding measuring response expectancy, we aligned the expected emotion with the experience of that emotion in a specific context. Response expectancy for relaxation was evaluated with a single item, consistent with the previous methodology (Kirsch, 2018; Montgomery & Bovbjerg, 2000). Specifically, participants were asked to report the expectancy magnitude with a question such as, "How much relaxation do you think/expect you will feel after the VR session? ". The strength of this expectancy was measured with the question, "How certain are you that you will feel relaxed after the VR session?". Response expectancy for positive emotions was calculated based on the sum of ten specific affects (interested, excited, strong, enthusiastic, pride, alert, inspired, determined, attentive, and active) derived from the Positive and Negative Affect Schedule (Watson et al., 1988). Each dimension—expected magnitude and strength of the expectancy—was assessed separately for these positive emotions. The responses were evaluated on an 11-point Likert scale (0 = not at all, 10 =to a great extent). Higher scores indicate higher levels of response expectancy for relaxation and response expectancy for positive emotions in general, corresponding to each sub-dimension. In this study, the internal consistency of the magnitude (α=.828) and strength (α=.863) of response expectancies for positive emotions was high.

2.2.3. Outcome variables: *Relaxation states, Positive Emotions and Physiological Indices*

Smith Relaxation States Inventory-3 (SRSI-3; Smith, 2010) measured relaxation states and perceived stress. Following a previous line of research (Meyer et al., 2022; Riva et al., 2020), we specifically selected only 12 items to assess the current relaxation state (rest/refresh, energized, physical relaxation, at ease/peace, joy, mental quiet, awareness). On a 6-point Likert scale, participants were instructed to rate each item by how they feel "right now" (1=not at all, 6=maximum). The Cronbach's alpha coefficient computed for the subscale was high, ranging from α =.85-.87.

Positive emotions were measured using the Positive Affect (PA) subscale from the Positive and Negative Affect Schedule (Watson et al., 1988). The PA subscale consists of ten positive mood adjectives, with scores ranging from 10 to 50, where higher scores indicate higher levels of positive affect. Crawford and Henry (2004) demonstrated that this scale has good psychometric properties for a non-clinical sample. In the current study, the internal consistency of the PA subscale was high (α = .847-.860).

Physiological measures were recorded using the Empatica E4 wristband (Empatica, Milan, Italy), a real-time physiological monitoring tool specifically designed for research. This advanced device collects high-quality data across various psychophysiological parameters, including heart rate (HR), heart rate variability (HRV), electrodermal activity (EDA), and skin temperature. In our study, HR, RMSSD, and SCL were continuously measured during the baseline phase and the emotion-induction procedure. HR, the most commonly utilized indicator of overall cardiovascular activity (Kreibig, 2010), was one of the key parameters we monitored. RMSSD, which measures the variability in heart rate from one heartbeat to the next, and SCL, the most commonly used electrodermal measure (Kreibig, 2010), were also recorded. The validity of physiological data collected with the E4 wristband under low-movement conditions in a laboratory setting was demonstrated in previous studies (Schuurmans et al., 2020; Stuyck et al., 2022).

2.2.4. Virtual Reality Environment

'Nature Treks VR' is an interactive commercial program developed by Greener Games, accessible at https://www.oculus.com/experiences/go/1723271804396968/. It's designed to immerse users in 15 natural environments, each accompanied by soothing instrumental music and sounds of nature. The program offers various locomotion options for exploring these environments, such as blink teleportation, free movement, and snap rotation. Users can personalize the weather, manipulate the time of day or night, and influence many aspects of the virtual world. Our experiment took place in the 'Green Meadows' environment, where we utilized the user index, background music, and a single functional controller for the dominant hand. The environment features grassy hills, flowers, a river, and animals like rabbits and deer.

2.3. Procedure

Online phase. Participants were recruited via online social networks, where they could access the study link. This link contained information about the study, informed consent, general information (e.g., demographic characteristics, clinical status, individuals' experiences with technology), and optimism as a dispositional trait (LOT-R). However, at this stage, the participants were screened for eligibility. The study was approved by the University's Institutional Review Board.

Experimental phase. Eligible participants attended a one-hour lab session. Before beginning the experiment, all participants received specific details about the procedure, and physiological data acquisition. The experimental phase contained two baseline measures, one without VR equipment (Natural Baseline) and one with VR equipment (VR baseline), respectively the VR session for inducing positive emotions and relaxation.

Baseline measures – Natural Baseline. Initially, the experimenter placed an E4 wristband on the participant's non-dominant wrist and began collecting physiological data for 5 minutes. The participant stood in the center of the room (Baseline without VR). During this time, participants were instructed to keep their wristband-wearing hand and body still, except for moving their heads from left to right. After this phase, participants completed the measures for T0 (SRSI-3 and PANAS-PA state).

Baseline measures - VR Baseline. Subsequently, participants were again invited to the middle of the room, where they were introduced to the Oculus VR headset and immersed in a VR-neutral space. While in this environment, physiological indices were collected for another 5 minutes After the VR baseline, the experimenter provided instructions for the VR session. Before the VR session, participants completed measures corresponding to T1 (Response Expectancies items, SRSI-3, and PANAS-PA state).

To enhance rigor, we introduced two types of baselines (Natural Baseline and VR Baseline).

VR session: Green Meadows. Participants were brought to the center of the room for the experimental part, where they were introduced to the Oculus controller. Following a brief training session, participants were instructed on accessing "Green Meadows" within the Nature Treks VR application. Each participant was required to confirm their understanding of exploring and interacting with the VR environment using the controller. The experimental session started and continued for 15 minutes, during which we continuously recorded physiological data. Throughout this phase, participants were advised to remain stationery and refrain from moving their hands or bodies while wearing the E4 wristband, except for turning their heads from left to right to navigate the VR environment. The experimenter remained in the room with the participant for the whole session and was available for assistance. Following the VR session, participants completed the final assessments corresponding to T2 (SRSI-3, and PANAS-PA state).

2.4. Preprocessing of psychophysiological data

BVP raw data were pre-processed in MATLAB to first extract the IBI time series and correct, upon visual inspection, ectopic and wrongly detected peaks, and then derive the cardiovascular measures of interest, namely heart rate (HR) and the root mean square of successive differences (RMSSD), for each part of the task. EDA raw data were pre-processed in MATLB using the Continuous Decomposition Analysis implemented in the LedaLab toolbox (Benedek & Kaernback, 2010) to estimate changes in the tonic skin conductance level (SCL) in each part of the task.

2.5. Data analysis plan

Descriptive statistics were calculated to explore demographic characteristics and target variables. To assess whether the VR session was effective in inducing positive outcomes and biological indexes of emotional response, a series of repeated measures ANOVAs were employed to analyse the changes in state relaxation, positive emotions, heart rate (HR), the root mean square of successive differences (RMSSD) and skin conductance level (SCL) during the emotion-induction procedure. The indirect association between optimism disposition and positive outcomes (relaxation states and positive emotions), as well as biological indexes of emotional response (HR, RMSSD and SCL), through Response Expectancy dimensions (magnitude and strength) was examined using a bootstrapping procedure (bias-corrected, with 5000 iterations) that assessed the indirect effects (Preacher & Hayes, 2008). An indirect association was considered present if the 95% bootstrapping confidence interval (CI) did not include zero. We tested eight parallel multiple mediation models based on model 4 from the SPSS PROCESS macro function (Hayes, 2017) for indirect association analysis. The statistical analyses for mediations models were performed using IBM SPSS Statistics, version 22 (IBM Corp, Armonk, NY, 2013).

3. Results

Manipulation check

A series of repeated measures ANOVAs were conducted to assess the suitability of the VR session as an induction procedure for the participants. The results indicated a significant effect of time on relaxation states, Huynh–Feldt corrected F (1.67, 224.98) = 108.07, $p < .001$, $\eta_p 2 = 0.44$; positive emotions, Huynh–Feldt corrected F (1.63, 219.69) = 16.16, $p < .001$, $\eta_p 2 = .108$; and SCL, Huynh–Feldt corrected F (1.90, 255.32) = 21.53, $p < .001$, $\eta_p 2 = .13$. In the case of HR, the assumption of sphericity was not violated, as evidenced by a non-significant Mauchly's Test of Sphericity ($p = .074$), indicating no need for corrections. The repeated measures ANOVA on HR revealed an F (2, 268) = 6.89, $p = .001$, $\eta_p 2 = .04$. In the case of RMSSD, Huynh–Feldt corrected F (1.90, 255.26) = .78, $p = .45$, $\eta_p 2 = .006$ result indicated no significant effect of time.

Pairwise comparisons with Sidak correction indicated a significant increase in the relaxation state from the natural baseline to the VR baseline (mean difference = −4.70, S.E. = .47, p < .001, 95% CI = −5.84, −3.55) and from the VR baseline to the VR session (mean difference = −3.69, S.E. = .53, p < .001, 95% CI = −4.99, −2.39). For positive emotions, pairwise comparisons (Sidak corrected) revealed a significant increase from the natural baseline to the VR baseline (mean difference = −1.34, S.E. = .31, p < .001, 95% CI = −2.11, −.58), with no other significant increases (p > .05). SCL level significantly decreased only from the VR baseline to the VR session (mean difference = .99, S.E. = .17, p < .001, 95% CI = .56, 1.41). For HR, pairwise comparisons (Sidak corrected) indicated a significant decrease from the natural baseline to the VR baseline (mean difference = 3.04, S.E. = 1.11, p = .02, 95% CI = .36, 5.73), with no other significant decreases (p > .05). For RMSSD, pairwise comparisons (Sidak corrected) revealed no significant change. However, current results indicate that the emotion-induction procedure successfully modulated relaxation and physiological responses.

Mediation Analysis

To assess the mediating effects of both dimensions of response expectancy (Response Expectancy Magnitude and Response Expectancy Strength), we employed multiple parallel mediation models, incorporating the mediators simultaneously in the same model. The indirect associations between optimism disposition and non-volitional outcomes (Relaxation States, Positive Emotion States, Heart Rate, RMSSD, and SCL) through response expectancies were examined using eight parallel mediation models (see Figure 2. Models 1.1 – 1.4, and Figure 3. Models 2.1 -2.4) implemented through PROCESS in SPSS. Table 3 presents the coefficients of the indirect effects along with the bootstrapping 95 % confidence intervals.

Response Expectancy Magnitude and Strength for Relaxation

When response expectancy magnitude for relaxation and response expectancy strength for relaxation were included, only response expectancy for relaxation magnitude significantly mediated the association between optimism and relaxation states, indirect effect = .12, S.E. = .06, 95% CI [.02, .26] (Table 3). Similarly, response expectancy for relaxation magnitude was found to significantly mediate the relationship between optimism and SCL, indirect effect = .01, S.E = .01, 95% CI [.0002, 0.04] (Table 3), while no response expectancy for relaxation dimension mediated the association between optimism and HR, respectively optimism and RMSSD (Table 3). Thus, as shown in Figure 2, the parallel mediation analysis illustrates optimism indirectly relates to relaxation states through response expectancy for relaxation magnitude and SCL through the same mediator.

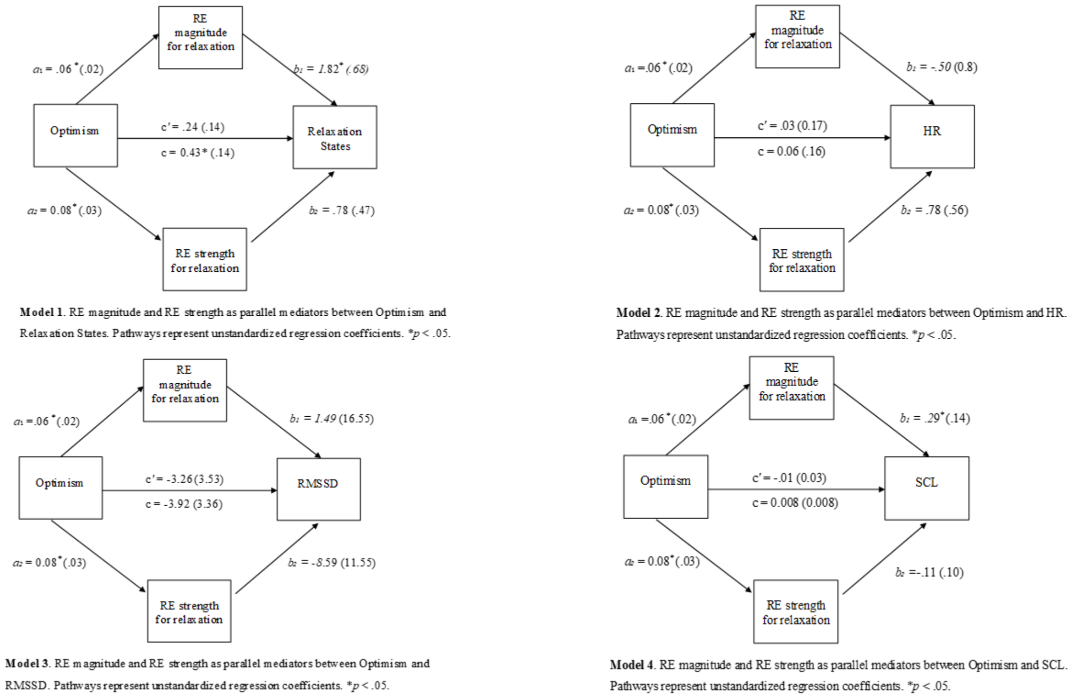

Figure 2. Model 1, 2, 3 and 4. RE magnitude and RE strength as parallel mediators between Optimism and Emotional and Physiological Outcomes (criterion variables: Relaxation States (*Model 1*), HR (Model 2), RMSSD (Model 3) and SCL (Model 4). Pathways represent unstandardized regression coefficients (**p* < .05).
The indirect association between Optimism and Relaxation States (Model 1), Optimism and HR (Model 2), Optimism and RMSSD (Model 3) and Optimism and SCL (Model 4) through two parallel mediates Response Expectancy Magnitude for relaxation (M1) and Response Expectancy Strength for relaxation (M2). The pathways represent unstandardized regression coefficients, with standard errors provided in brackets. Path a_1 indicates the association between Optimism and RE magnitude. Path a_2 indicates the association between Optimism and RE strength. Path b_1 illustrates the association between RE magnitude and emotional and physiological outcomes (criterion variables: Relaxation States, HR, RMSSD and SCL). Path b_2 illustrates the association between RE strength and emotional and physiological outcomes (criterion variables: Relaxation States, HR, RMSSD and SCL). c represents the total association path; c' denotes the direct association path; **p < .05*.

Table 3. The indirect association between optimism disposition and non-volitional outcomes (relaxation states, Positive Emotions, HR, RMSSD, SCL) through Response Expectancy Magnitude and Strength

Outcomes	Mediators	B	SE (B)	95% CI
Relaxation States	Total indirect	0.19	0.06	[0.070, 0.335]
	RE Magnitude for relaxation	0.12	0.06	[0.021, 0.262]
	RE Strength for relaxation	0.06	0.05	[-0.027, 0.191]
HR	Total indirect	0.03	0.05	[-0.075, 0.151]
	RE Magnitude for relaxation	-0.03	0.05	[-0.154, 0.055]
	RE Strength for relaxation	0.06	0.04	[-0.012, 0.186]
	Total indirect	-0.66	0.69	[-2.254, 0.484]
RMSSD	RE Magnitude for relaxation	0.09	0.42	[-0.738, 0.961]
	RE Strength for relaxation	-0.76	0.54	[-2.017, 0.088]
SCL	Total indirect	0.009	0.009	[-0.006, 0.030]
	RE Magnitude for relaxation	0.01	0.01	[0.0002, 0.045]
	RE Strength for relaxation	-0.01	0.007	[-0.026, 0.003]
Positive emotions	Total indirect	0.10	0.07	[-0.032, 0.262]
	RE Magnitude for positive emotions	0.10	0.07	[-0.033, 0.249]
	RE Strength for positive emotions	0.005	0.02	[-0.034, 0.050]
HR	Total indirect	0.03	0.03	[-0.034, 0.122]
	RE Magnitude for positive emotions	0.04	0.04	[-0.017, 0.142]

	RE Strength for positive emotions	-0.005	0.03	[-0.091, 0.070]
	Total indirect	-1.04	1.54	[-5.104, 0.565]
RMSSD	RE Magnitude for positive emotions	-0.38	0.39	[-1.322, 0.139]
	RE Strength for positive emotions	-0.66	1.29	[-3.994, 0.871]
SCL	Total indirect	-0.002	0.004	[-0.011, 0.008]
	RE Magnitude for positive emotions	0.005	0.006	[-0.002, 0.021]
	RE Strength for positive emotions	-0.007	0.005	[-0.021, 0.0008]

Notes: B, unstandardized regression coefficient; SE, standard deviation; 95% CI, 95% bootstrapping confidence interval

Response Expectancy Magnitude and Strength for Positive Emotions

When response expectancy magnitude for positive emotions and response expectancy strength for positive emotions were included, neither dimension significantly mediated the associations between optimism and positive emotions, optimism and HR, optimism and RMSSD, or optimism and SCL (Table 3). Direct and indirect associations between optimism disposition and non-volitional outcomes were non-significant in this mediation's models (see Figure 3. Models 1, 2, 3, and 4).

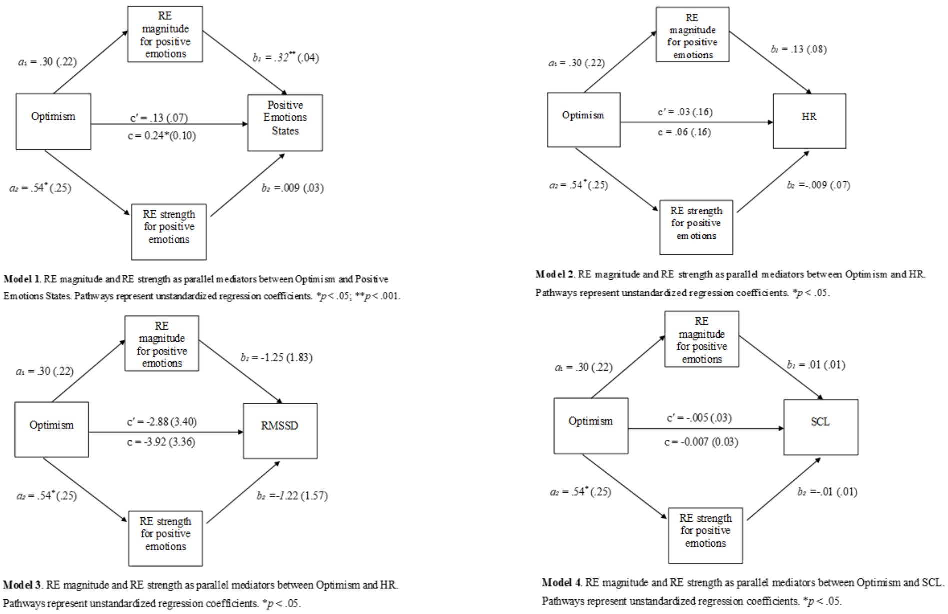

Figure 3. Model 1, 2, 3 and 4. RE magnitude and RE strength as parallel mediators between Optimism and Emotional and Physiological Outcomes (criterion variables: Positive Emotions States (*Model 1*), HR (Model 2), RMSSD (Model 3) and SCL (Model 4). Pathways represent unstandardized regression coefficients (*$p < .05$).
The indirect association between Optimism and Positive Emotions States (Model 1), Optimism and HR (Model 2), Optimism and RMSSD (Model 3) and Optimism and SCL (Model 4) through two parallel mediates Response Expectancy Magnitude for positive emotions (M1) and Response Expectancy Strength for positive emotions (M2). The pathways represent unstandardized regression coefficients, with standard errors provided in brackets. Path a_1 indicates the association between Optimism and RE magnitude. Path a_2 indicates the association between Optimism and RE strength. Path b_1 illustrates the association between RE magnitude and emotional and physiological outcomes (criterion variables: Positive Emotions States, HR, RMSSD and SCL). Path b_2 illustrates the association between RE strength and emotional and physiological outcomes (criterion variables: Positive Emotions States, HR, RMSSD and SCL). c represents the total association path; c' denotes the direct association path; *$p < .05$.

Discussion

The main goal of the current study was to explore the role of response expectancy as a mediator in the relation between optimism and non-volitional outcomes, employing a VR positive mood induction method. More specifically, this study explored the magnitude and the strength response expectancies dimensions as concurrent mediators between optimism disposition and emotional and psychological outcomes experienced during VR mood induction.

Virtual Reality session efficacy

As expected, the VR nature experience enhanced relaxation, as demonstrated by self-report measures and objective indicators such as skin conductance. These results align with existing literature on subjective relaxation outcomes (Adhyaru & Kemp, 2022; Riches et al., 2023; Villani et al., 2007; Villani & Riva, 2008; Xu et al., 2023) and objective measures of physiological arousal, including skin conductance levels (e.g., Anderson et al., 2017). In contrast, our study found no significant change in positive emotions and heart rate levels after the VR nature experience. These finding contrasts previous studies (Adhyaru & Kemp, 2022; Anderson et al., 2017; Chan et al., 2023; Manchón & Šimunić, 2023; McGarry et al., 2023). The discrepancy in findings related to positive emotional outcomes might be due to differences in the specific emotions examined in previous studies. For instance, studies like those by Manchón and Šimunić (2023) and Adhyaru and Kemp (2022) focused on distinct emotions, such as happiness, which appeared to be more significantly influenced by the experience of a natural environment created in VR. In our study, however, positive emotions were assessed using the positive affect subscale from PANAS (Watson et al., 1988), which comprises the total score based on ten specific emotions characterized by high arousal levels (McManus et al., 2019). The VR nature experience seems to be more relevant for increasing low-arousal positive emotions, such as relaxation, rather than high-arousal positive emotions, such as enthusiasm and determination. This difference in the type of positive emotions assessed could explain the variation in outcomes between our study and previous research.

Furthermore, methodological differences, such as the absence of a baseline level for accurately tracking the temporal evolution of outcomes (within-subject factor), as noted in Chan and collab. (2023) could have explained the differences results obtained in our study. Regarding the non-significant findings for heart rate, methodological variations across studies could account for the discrepancies with prior research. Factors such as the type of baseline condition (e.g., passive relaxation vs. passive relaxation in a neutral VR environment), participant posture during data collection or intervention (seated vs. standing), and the time intervals used for analyzing physiological indices might have played a role. For instance, McGarry et al. (2023) reported a significant reduction in heart rate levels after a VR session, using the average heart rate data points collected over a short interval (30 seconds) before and after the VR session. These methodological differences, including the length and conditions of data collection, may explain the non-significant findings for heart rate in the present study.

Mediation effect

The parallel mediation models provide insight into how optimism influences non-volitional outcomes through two response expectancy dimensions.

Response Expectancy Magnitude and Strength for Relaxation

In the case of response expectancy for relaxation, where the magnitude and strength dimensions were considered parallel mediators, four models were tested to explore the relations between optimism and non-volitional outcomes. Findings revealed that two of the tested models were significant, while the others were not. Specifically, the results showed that the response expectancy magnitude for relaxation (M1) served as a full mediator in the relationship between optimism and relaxation states. In other words, individuals with higher levels of optimism experienced greater relaxation states, but this relationship was significantly influenced by the expected magnitude for relaxation states. Additionally, the response expectancy magnitude for relaxation (M1) also fully mediated the relationship between optimism and skin conductance levels. Skin conductance level is a physiological measure commonly used to assess emotional arousal, with lower levels indicating lesser arousal. This finding suggests that optimistic individuals who had a higher expectancy of relaxation not only reported feeling more relaxed but also exhibited physiological signs of relaxation, as evidenced by decreases in their skin conductance levels.

Thus, these findings suggest that having generalized positive expectancies about the future (being optimistic) does not automatically lead to positive outcomes, such as experiencing relaxation in a specific context. Instead, it appears that a high level of response expectancy magnitude for relaxation is essential for achieving relaxation states, both subjectively (as felt by the individual) and objectively (as measured by decreased skin conductance level). Our results are in accordance with previous studies that indicated a positive association between optimism, considered a more generalised positive expectation from future, and expected magnitude for relaxation (response expectancy) (e.g., Dilorenzo et al., 2011). Additionally, Sucala and Tatar (2010) demonstrated that negative mood regulation expectancies (a subtype of response expectancy) completely mediate the impact of pessimism on depression and anxiety symptoms. The direct relationship between response expectancy for relaxation and the actual state of relaxation may be explained by considering these expectations as particular beliefs within the response expectancy model (e.g., Kirsch, 1985; 1990; 1997).

The other tested models showed that neither the magnitude nor the strength dimensions of response expectancy for relaxation were significant mediators in the relationships between optimism and HR or between optimism and the RMSSD. Specifically, these findings suggest that the impact of optimism on heart rate variability and overall autonomic control, as measured by HR and RMSSD, does not operate through response expectancy for relaxation as it does for skin conductance responses. This observation may indicate differences in how cognitive expectations affect various physiological processes or imply that other mediators or mechanisms are involved in these particular relationships.

Response Expectancy Magnitude and Strength for Positive Emotions

When examining the impact of response expectancy for positive emotions, with both magnitude and strength as potential parallel mediators, four models were evaluated to investigate the associations between optimism and non-volitional outcomes (see Figure 3). The results showed that none of these models were significant. Specifically, the models examining the dimensions of response expectancy—magnitude (M1) and strength (M2)—indicated that these factors do not mediate the relationship between optimism and positive emotions. These findings were consistent across both subjective assessments (positive emotions states) and physiological measures (SCL, HR and RMSSD). In other words, optimism did not influence positive emotions through changes in the anticipated intensity and strength of these emotional responses. A possible explanation for this result might be that some items used to measure positive expectancies (where a mean score was calculated) and the experience of positive emotions (where a mean score was also calculated) were perceived as too general or abstract regarding the context. Notably, the positive emotions included were characterized by high arousal (McManus et al., 2019; Russell, 1980) and were measured by the Positive Affect subscale of the PANAS (Watson et al., 1988). Future studies should include more sensitive and context-specific measures of response expectancy for specific positive emotions, as well as for particular emotional experiences. However, the VR nature session seems to be more relevant in enhancing relaxation states than high-arousal positive emotions. However, the VR nature session seem to be more relevant in enhancing relaxation states than positive emotions.

Limitations and Future directions

The study employed a cross-sectional design, inherently limiting its capacity to establish causal relationships between variables. Future research should consider adopting an experimental paradigm that manipulates response expectancy or a longitudinal design. The participants in this study were primarily recruited through social media and university groups, resulting in a convenience sample. Moreover, most of these participants were healthy individuals from collectivistic cultures and predominantly women, which may restrict the generalizability of our findings. Therefore, future studies should endeavour to recruit a more diverse and gender-balanced sample to ensure the broader applicability and relevance of the results.

Despite the limitations mentioned above, the study has the following important contributions. This is the first study to address the relevance of response expectancy magnitude and strength dimensions concurrently as associates of non-volitional outcomes in individuals exposed to a positive VR session based on a natural environment. From a theoretical perspective, the current findings offer several notable contributions. First, when both the magnitude and strength dimensions of response expectancy are tested within the same model, the magnitude dimension emerges as the significant mediator between an optimistic disposition and the relaxation states experienced during a session in a laboratory setting.

Conclusions

The results of our study have confirmed the efficacy of the "Green Meadows" virtual reality experience in promoting relaxation and specific psychological responses in healthy individuals. The key findings showed significant enhancements in relaxation states, as well as physiological markers indicating a stress reduction, such as a decrease in skin conductance level (SCL) and the relaxing impact, noticed in changes in heart rate (HR) and the variability between heartbeats interval (RMSSD) compared with baseline measures. The parallel mediation analysis explored the role of response expectancies (both magnitude and strength dimension) in mediating the relationship between optimism disposition and various non-volitional outcomes (relaxation, positive emotions, HR, RMSSD, and SCL). Our findings revealed that only the magnitude of response expectancy for relaxation significantly mediated the relationship between optimism and relaxation, and between optimism and SCL. This suggests that individuals with a higher optimism disposition are likely to experience enhanced relaxation and increased physiological arousal, as SCL indicated, partly due to their greater response expectancy magnitude for experiencing relaxation. However, the response expectancy dimension (magnitude and strength) did not significantly mediate the relationship between optimism and positive emotions, HR, or RMSSD, indicating the specificity of optimism's effects on specific psychological and physiological responses.

Study 3: Reciprocal Relationships between Positive Expectancies and Positive Emotions during the COVID-19 Pandemic: A Cross-Lagged Panel Study

1. Introduction

The global COVID-19 pandemic and its effects, which included a new set of challenges in social relationships, health, finances, and lifestyle, were a significant source of stress for numerous individuals worldwide and had a significant influence on their cognitive and emotional functioning. According to Folkman and Moskowitz (2000), resilient responses during such times of adversity are defined, in part, by the use of positive emotions.

Extensive research has shown that positive emotional experiences are adaptive and contribute to helping individuals recover from both minor and major life stressors (Fredrickson et al., 2003; Ong et al., 2006; Revord et al., 2021). In addition, recent research has demonstrated the positive functions of positive emotions, demonstrating a buffering, bolstering, and building effect of positive emotions in the context of COVID-19 (Israelashvili, 2021; Sandin & Garcia-Escalera, 2020; Waters et al., 2021).

Due to the importance of positive emotions in coping with stress, it is crucial to evaluate specific protective factors that predict the experience of positive emotions during stressful situations. Identifying these protective factors can further guide policies and interventions to target these processes in individuals facing adversities, such as the COVID-19 pandemic, and protect their psychological well-being. Thus, in the current longitudinal investigation, we focused on positive expectancies towards the future (optimism, response expectancy, and response hope) in relation to the experience of positive emotions during the COVID-19 pandemic.

The focus on optimism, response expectancy, and response hope in this study is based on the well-documented relationship between cognition and emotion (David et al., 2002). Research suggests that positive cognition, which includes optimism, response expectancy, and response hope, plays a crucial role in influencing positive emotions (Cristea et al., 2011; David et al., 2010; Dilorenzo et al., 2011). While other factors are relevant, we prioritize positive cognition due to its substantial impact on positive emotions within the cognition-emotion framework. Furthermore, within the domain of positive cognition, certain factors, like optimism, have been extensively studied, whereas others, such as response expectancy and response hope, have received less attention in the existing literature. This research aims to bridge this gap and provide a comprehensive perspective on how these factors interact and contribute to the experience of positive emotions. Not least, previous research has also highlighted the important clinical relevance of these factors, which can be further addressed in therapy.

1.1. Optimism

Optimism is defined as a relatively stable tendency to anticipate positive rather than negative outcomes in uncertain situations (Scheier et al., 1994). Solberg (2016) proposed that optimism has a protective function and may act as a "buffer" against the adverse effects of stressful events. Recently, research showed that optimism mediates the relationship between coronavirus stress and meaning in life, suggesting that optimism can mitigate the adverse effects of coronavirus stress (Arslan & Yıldırım, 2021). However, previous studies showed that optimism, being a dispositional trait, impacts the experience of positive emotions in the long term rather than the short term (Jovanović et al., 2021). In addition, a recent longitudinal study spanning two decades demonstrated that optimism predicts long-term positive affect (14 years or more later) in a sample of men from the Veterans Affairs Normative Aging Study (Lee et al., 2022). Based on these findings, we hypothesize that optimism can be operationalized as a dispositional tendency that predicts the experience of positive emotions in the long run as opposed to the short run during the COVID-19 pandemic.

1.2. Response expectancy

According to the Response Expectancy Theory proposed by Kirsch (1985), response expectancy is defined as the anticipation of a specific outcome or response that an individual expects to occur in a particular situation or context. According to this theory, response expectancies (1) are sufficient to determine a non-volitional outcome, (2) are not mediated by other psychological mediators, and (3) are self-confirming. Non-volitional outcomes can include emotional reactions (e.g., relaxation) and other subjective states (e.g., pain and fatigue as a side effect of chemotherapy). For example, anticipating feeling relaxed in a given situation can often result in one feeling relaxed in that particular situation.

Numerous studies support the important role of response expectancy, demonstrating a positive association between this construct and a variety of non-volitional responses, such as pain, fatigue (Devlin et al., 2017), distress (Dilorenzo et al., 2011), public speaking anxiety (Podină & Vîslă, 2014;), and positive emotions (Cristea et al., 2011). Furthermore, a recent meta-analysis revealed a medium to large effect size for the relation between response expectancy and negative emotions and a medium effect size for the relation between response expectancy and positive emotions (Coteţ & David, 2016). Thus, response expectancy plays an important role in determining the occurrence of various outcomes, including emotional outcomes. While previous studies focused predominantly on negative emotional outcomes, the current study aimed to broaden previous research by focusing on positive emotional outcomes. This is especially relevant also in the context in which positive emotions have an important protective role in adverse situations. However, previous research showed that response expectancy, being a state variable, impacts the experience of positive emotions in the short term rather than the long term (Kirsch, 1990).

Thus, in the current study, we investigated the role of response expectancy for positive emotions in determining the experience of positive emotions at two points during the COVID-19 pandemic. Specifically, we hypothesize that response expectancy for positive emotions will significantly predict the experience of positive emotions in the short term rather than in the long term.

1.3. Response hope

According to prior research, response hope refers to the desire for a non-volitional outcome to occur (or not) in a particular situation or context, which can encompass a range of emotional states or physical sensations (e.g., distress, fatigue, relaxation) (Anton & David, 2013; David et al., 2006; Frank & Frank, 1993). Current research supports the important role of response hope in relation to various outcomes, both positive and negative, which extend to a broad spectrum of emotional experiences, such as distress, and positive emotions (Cristea et al., 2011; David et al., 2006). With respect to positive emotions, one study indicates that individuals with high levels of response hope for positive emotions may be more likely to experience positive emotions, even in the face of adversity (Cristea et al., 2011). However, another study found no significant association between response hope for positive emotions and positive emotions (Anton & David, 2013). Being a state variable, response hope mainly impacts the experience of positive emotions in the short term rather than the long term (Cristea et al., 2011), similar to response expectancy. Therefore, in this study, aligning with the initial hypotheses of the theory of response hope (David et al., 2006) rather than the mixed results in the literature, we hypothesized that response hope for positive emotions would have a greater impact on predicting short-term positive emotions rather than long-term positive emotions.

Furthermore, David and collaborators (2006) have proposed that a discrepancy between response hope and response expectancy can directly influence an individual's emotional reactions to a given situation and can be a source of positive emotions or distress. The authors developed a discrepancy score by subtracting an individual's response expectancy from their response hope. For example, if an individual comes home from work and hopes to feel very joyful but expects to experience very little joy, the resulting discrepancy score would be positive. This positive discrepancy score between response hope and response expectancy regarding a positive emotion would result in a low level of positive emotions or a high level of distress for the individual (i.e., the individual will be extremely dissatisfied in a situation where expectations are far from desires). Conversely, if an individual hopes to feel little joy upon returning home but expects to experience high levels of joy, the discrepancy score would be negative. This negative discrepancy score between response hope and response expectancy regarding a positive emotion would be a source of positive emotions or low distress level (i.e., the individual will be extremely satisfied in a situation where hopes are far exceeded by expectations) (David et al., 2006). Thus, regarding the discrepancy between response hope and response expectancy for positive emotions, in the current study, we hypothesized that a positive discrepancy score would result in a lower level of positive emotions experienced during the COVID-19 pandemic.

1.5. Overview of the present study

According to previous research, optimism, response expectancy, response hope, and the discrepancy between response hope and response expectancy are expectancies that have a distinct and significant impact on non-volitional outcomes, such as emotions. In the current study, we aim to investigate whether each construct contributes uniquely and/or best predicts the experience of positive emotions. In addition, we will explore the dynamic relationships between all these variables.

From a general perspective, the primary objective of this study was to determine which types of expectancies best predict positive emotions in the short and long term during the COVID-19 pandemic. We expected dispositional optimism to be a stronger predictor of longer-term outcomes, whereas specific expectancies (response expectancy, response hope, and discrepancy score) would be a better predictor of shorter-term outcomes.

On the other hand, it is widely acknowledged that emotions play a significant role in how individuals process information about the world, influencing their beliefs, attitudes, and behaviors (Ashby et al., 1999; Ceccato et al., 2021; Fredrickson et al., 2008). Emotions can also influence expectations, including optimism (Ceccato et al., 2021; Yang, 2022). For instance, Yang (2022) demonstrated that positive emotions are predictive of optimism for both the present day and the following day. Furthermore, the differentiation of positive emotions strengthens the positive relation between positive emotions and state optimism. Additionally, Kyriazos and collaborators (2021) found that the presence of positive emotions predicted short-term optimism during the early days of the COVID-19 quarantine. Similarly, Jovanović and collaborators (2021) showed that experiencing positive emotions predicted greater levels of optimism six months and two years later. Thus, these studies show that optimism can be positively influenced by positive emotions, in addition to the previously established notion that optimism can positively influence emotions. Therefore, we hypothesize that positive emotions will predict optimism in both the short term and the long term. Regarding the investigation of the impact of positive emotions on response expectancy and response hope, to our knowledge, there are no prior studies addressing this issue. Consequently, we have not developed any explicit hypotheses in this regard. In view of this gap in the existing literature, our current study is aimed at examining the bidirectional relationships between positive emotions and positive expectancies.

In more specific terms, in the current study, we examined the relationships between different positive expectations (optimism, response expectancy, and response hope) and positive emotions assessed at three-time points during the COVID-19 pandemic (T1: lockdown period; T2: two weeks later, corresponding to the urgency period with moderate restrictions, and T3: four months later, corresponding to the alert period with maintained moderate restrictions). To do this, we tested four cross-lagged models to illustrate (1) the best predictor for positive emotions and (2) reciprocal influences between variables. In Model 1, we investigated the relations between response expectancy, response hope, optimism, and positive emotions at T1 and T2 (at two weeks - short term). Model 2 analyzed the same variables at T1 and T3 (four months later - long term). In Model 3 and Model 4, we tested the relations between the discrepancy score (response hope - response expectancy for positive emotions), optimism, and positive emotions experienced at T1 and T2, respectively, at T1 and T3. To our knowledge, this is the first study that integrates all variables in a longitudinal design with the potential to increase our understanding of these protective factors relevant to resilience during times of crisis, such as COVID-19.

2. Methods

2.1. Participants

The initial sample consisted of 271 participants recruited between March and April 2020, during the period when Romania declared a state of emergency and imposed a lockdown. However, in the final sample, we included 249 participants who completed the measurements (T1), as 22 participants were excluded for not meeting the inclusion criteria (see details below). Thus, the final sample at T1 comprised 211 females (84.7%) and 38 males (M=29.2, SD=9.92), aged 18-67.

Two weeks after the initial measurements (T2), participants completed the measurements again. During this phase, 131 participants from the initial 249 remained, consisting of 113 women (89%) and 14 men aged 19-52 (M=28.53, SD=8.99). This period in Romania corresponded to the alert phase, characterized by moderate restrictions.

Finally, four months later (T3), 74 participants out of 131 participants at T2, 64 females (86.5%) and 10 males, aged 19-52 years (M=28.75, SD=9.2), still completed the measurements for the last time. The decision regarding the necessary sample size for our study was guided by a rule of thumb inspired by Boomsma's work (1985). Specifically, it was recommended that sample sizes exceeding N > 200 are sufficient for Structural Equation Modeling to prevent convergence issues and the occurrence of "Heywood cases". Inclusion criteria included (1) consent to participate in the study, (2) being at least 18 years old, and (3) the absence of suicidal ideation and self-harm behavior.

2.2. Data collection

Participants were recruited via online social networks (e.g., Facebook). Participants accessed a link through which they completed a survey containing demographic and psychological scales. Informed consent was provided as part of the online form. Participants who completed the first wave and expressed interest in participating in the subsequent measures were contacted again. The University's Institutional Review Board approved the study.

2.3. Measures

Optimism. The Life Orientation Test-Revised (Scheier et al., 1994) was used to measure optimism. The LOT-R was used as a unidimensional construct as was primarily recommended (Cano-García et al., 2015; Hinz et al., 2021). The score was calculated by adding the optimism and reversed pessimism scores. Scores range from 0 to 24; higher scores indicate higher levels of optimism. The LOT-R proved a suitable instrument with good psychometric properties (Hinz et al., 2021), while the internal consistency of optimism for the current study was high (α=.830 - .877).

Specific Expectancies for Positive Outcomes. Participants' response expectancies and hopes were evaluated with two items, consistent with the previous methodology (Montgomery & Bovbjerg, 2000). Research highlighted that single-stem measures are valid, reliable (Allen et al., 2022; Ang & Eisend, 2018), and acceptable for unidimensional constructs (Fuchs & Diamantopoulos, 2009). Specifically, participants were asked to report their expectations and hope for positive outcomes (e.g., How many positive emotions do you expect/hope to feel during the pandemic context?). The answers were anchored on 5-point Likert scales (1=not at all, 5=to a great extent). Higher scores indicate higher levels of response expectancies and response hope. The score for the discrepancy between response hopes and response expectancy regarding positive emotions was calculated by subtracting the score for response expectancies from the score for response hopes.

Positive emotions. A subscale with 13 items from the Profile of Affective Distress (Opris & Macavei, 2007) was used to measure positive emotions. Participants were required to indicate, using a 5-point Likert scale (1=not at all, 5=extremely), how frequently they experienced various positive emotions during the last two weeks in the context of the pandemic. The PAD has good psychometric properties and is a scale developed and validated on the Romanian population (Opris & Macavei, 2007). In the current study, the internal consistency of positive emotions was high (α=0.945 - 0.959).

2.4. Data analysis plan

All analyses were conducted in RStudio (*RStudio | Open Source & Professional Software for Data Science Teams*, n.d.). First, we explored the univariate and multivariate normality assumptions. We also computed the percentage of missing values. Inferential statistical analyses were conducted within the Structural Equation Modeling (SEM) framework. Specifically, we have specified four cross-lagged models. As data have not complied with the multivariate normality assumption, we used the maximum likelihood robust (MLR) estimator. MLR could provide accurate parameter estimates when data is not normally distributed, and it is also appropriate with ordinal data (five or more-level Likert scales) (Satorra & Bentler, 1994). The large percentage of missing data was handled via multiple imputations by chained equations (MICE), the state-of-the-art method for handling missing data (Buuren, 2018). By using MICE, one could generate multiple plausible values to replace the missing ones and combine these values (which take into account the uncertainty of values that are not available) for computing unbiased parameter estimates (Buuren, 2018). Rubin's rules were used for pooling point, and SE estimates across multiple imputed datasets and for computing the degrees of freedom for each t-test of the parameters (Rubin, 2004). Based on the rule of thumb that the number of imputations should be at least as large as the percent of missing values (Buuren, 2018), we used 50 imputations for short-term effect models (that is, T1 and T2) and 70 for the long-term effect models (that is, T1 and T3).

3. Results

3.1. *Preliminary analyses*

Descriptive statistics and correlation coefficients are presented in **Table 2**, and Pearson correlation coefficients are presented in **Table 3**. Univariate normality has been supported as the values of Skewness and Kurtosis for the variables included in the study were in the acceptable range (-2 to +2). However, the multivariate normality was not met as the Henze-Zirkler test was statistically significant ($p < .020$). Regarding missing data, the dropout percentage from T1 to T2 was 49%, while between T1 and T3 was 70%.

Table 2. Descriptive statistics

Measures	***Mean***	***SD***
Time 1		
RE for positive emotions	3.17	.91
RH for positive emotions	3.67	.97
Discrepancy Score	.50	.91
Optimism	15.61	4.66
Positive emotions	37.55	10.32
Time 2		
RE for positive emotions	3.26	.89
RH for positive emotions	3.91	.85
Discrepancy Score	.65	.80

Optimism	15.48	4.72
Positive emotions	40.35	11.03
Time 3		
RE for positive emotions	3.28	.89
RH for positive emotions	4.05	.85
Discrepancy Score	.77	.67
Optimism	15.60	4.88
Positive emotions	41.52	11.06

Note. RE = Response Expectancy for positive emotions; RH = Response Hope for positive emotions; Discrepancy Score = Response Hope - Response Expectancy; OPT = Optimism.

Table 3. Pearson correlation coefficients between the variables included in tested models

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. RE for positive emotions_T1	-														
2. RE for positive emotions_T2	.57**	-													
3. RE for positive emotions_T3	.53**	.40**	-												
4. RH for positive emotions_T1	.53**	.30**	.25*	-											
5. RH for positive emotions_T2	.48**	.58**	.43**	.48**	-										
6. RH for positive emotions_T3	.29*	.18	.70**	.23*	.49**	-									
7. OPT_T1	.37**	.34**	.31**	.29**	.25**	.13	-								
8. OPT _T2	.39**	.38**	.40**	.22**	.28**	.19	.83**	-							
9. OPT _T3	.45**	.41**	.40**	.19	.35**	.19	.78**	.82**	-						
10. Positive emotions_T1	.52**	.51**	.38**	.43**	.44**	.29**	.40**	.50**	.38**	-					
11. Positive emotions_T2	.50**	.58**	.44**	.32**	.50**	.40**	.39**	.53**	.42**	.74**	-				
12. Positive emotions_T3	.39**	.48**	.46**	.33**	.36**	.40**	.45**	.47**	.51**	.44**	.56**	-			
13. Discrepancy Score_T1[a]	-	-	-	-	-	-	-.06	-.15	-.24*	-.06	-.16	-.04	-		
14. Discrepancy Score_T2[a]	-	-	-	-	-	-	-.11	-.12	-.09	-.09	-.11	-.14	.29**	-	
15. Discrepancy Score_T3[a]	-	-	-	-	-	-	-.25*	-.29*	-.29*	-.12	-.08	-.10	.28*	.42*	-

Note. T1 = 249, T2 = 127 and T3 = 74 participants; RE = Response Expectancy for positive emotions; RH = Response Hope for positive emotions; OPT = Optimism; Discrepancy Score = Response Hope - Response Expectancy.

3.2. Associations Between Positive Expectancies and Positive Emotions at Two Weeks

The autoregressive paths were significant for Response Hope ($p < .001$), Response Expectancy ($p < .001$), Positive Emotions ($p < .001$), and Optimism ($p < .001$). The statistically significant cross lagged paths were between Response Expectancy at T1 and Positive Emotions at T2 ($p < .017$), Response Expectancy at T1 and Response Hope at T2 ($p < .012$), Positive Emotions at T1 and Response Hope at T2 ($p < .023$), Positive Emotions at T1 and Response Expectancy at T2 ($p < .002$), Response Expectancy at T1 and Optimism at T2 ($p < .016$), Positive Emotions at T1 and Optimism at T2 ($p <.005$) and Response Hope at T1 and Optimism at T2 ($p <.038$) (see Figure 1).

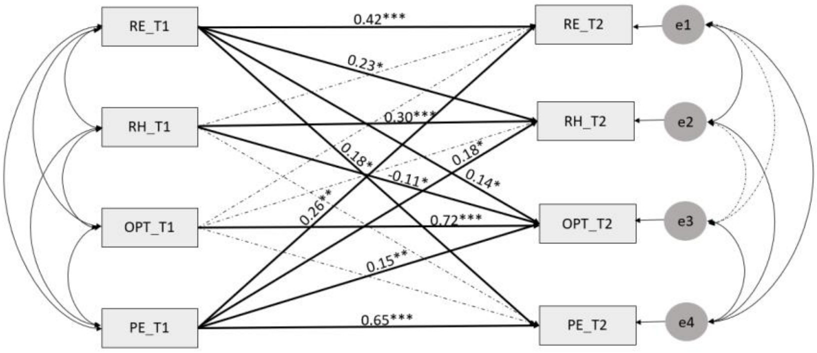

Figure 1. Model 1 with its paths at two weeks (T1-T2): auto-regressive paths and cross-lagged paths. *Note.* RE = Response Expectancy for positive emotions; RH = Response Hope for positive emotions; OPT = Optimism; and PE = Positive emotions; All outcomes are controlled for using covariates from the propensity model; *** p < 0.001, ** p < 0.05, * p < 0.01.

3.3. Associations Between Positive Expectancies and Positive Emotions at Four Months

The autoregressive paths were significant for Response Expectancy ($p < .001$), Positive Emotions ($p < .035$), and Optimism ($p < .001$). The statistically significant cross-lagged paths were between Optimism at T1 and Positive Emotions at T3 ($p < .04$), Response Expectancy at T1 and Optimism at T3 ($p < .017$) and Response Hope at T1 and Optimism at T3 ($p < .041$) (see Figure 2).

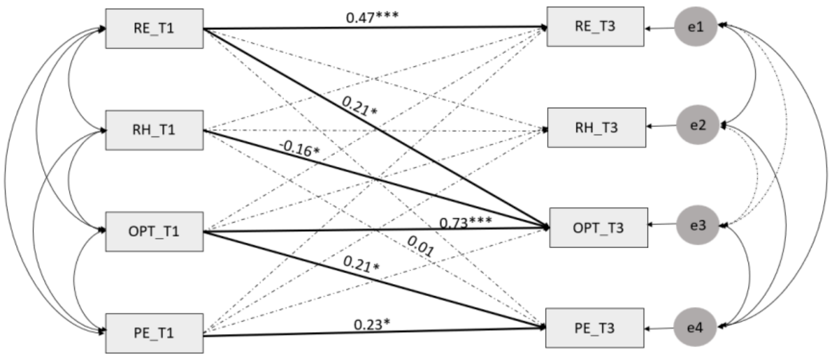

Figure 2. Model 2 with its paths at four months (T1-T3): auto-regressive paths and cross-lagged paths. *Note.* RE = Response Expectancy for positive emotions; RH = Response Hope for positive emotions; OPT = Optimism; and PE = Positive emotions; All outcomes are controlled for using covariates from the propensity model; *** p < 0.001, ** p < 0.05, * p < 0.01.

3.4. Associations Between Discrepancy Score, Optimism, and Positive Emotions at Two weeks

The autoregressive paths were significant for Discrepancy Score ($p < .001$), Optimism ($p < .001$) and Positive Emotions ($p < .001$). The statistically significant cross lagged paths were between Discrepancy Score at T1 and Positive Emotions at T2 ($p < .035$), Positive Emotions at T1 and Optimism at T2 ($p < .001$) and Discrepancy Score at T1 and OPT_T2 ($p < .008$) (see Figure 3).

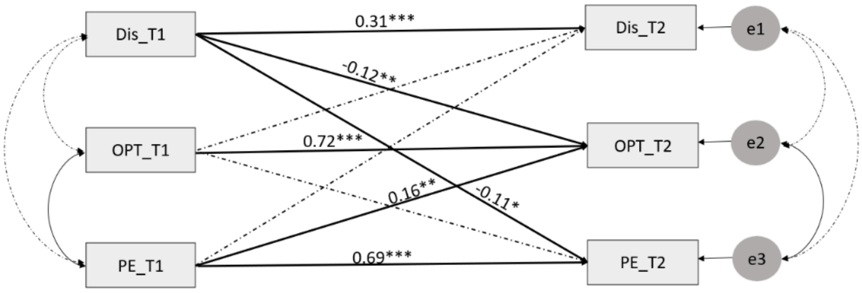

Figure 3. Model 3 with its paths at two weeks (T1-T2): auto-regressive paths and cross-lagged paths. *Note.* DIS = Discrepancy Score (Response Hope - Response Expectancy); OPT = Optimism; and PE = Positive emotions; All outcomes are controlled for using covariates from the propensity model; *** p < 0.001, ** p < 0.05, * p < 0.01.

3.5. Associations Between Discrepancy Score, Optimism, and Positive Emotions at Four months

The autoregressive paths were significant for Optimism ($p < .001$) and Positive emotions ($p < .012$) and were not significant for Discrepancy Score ($p < .33$). The statistically significant cross lagged paths were between Optimism at T1 and Positive emotions at T3 ($p < .004$) and for Discrepancy Score at T1 and Optimism at T3 ($p < .012$) (see Figure 4).

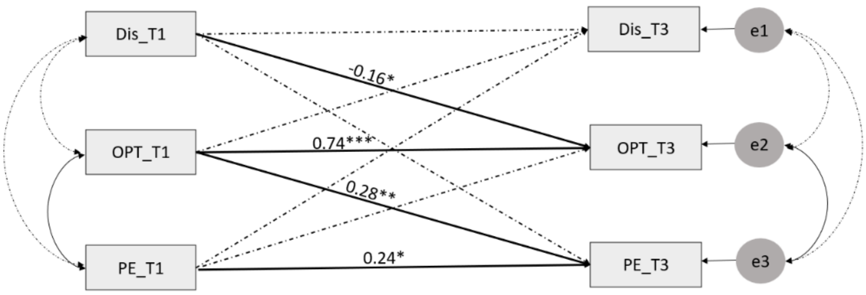

Figure 4. Model 4 with its paths at four months (T1-T3): auto-regressive paths and cross-lagged paths. *Note.* DIS = Discrepancy Score (Response Hope - Response Expectancy); OPT = Optimism; and PE = Positive emotions; All outcomes are controlled for using covariates from the propensity model; *** p < 0.001, ** p < 0.05, * p < 0.01.

4. Discussion

This study investigated whether positive expectancies (optimism, response expectancy, response hope, discrepancy score) have distinct and unique contributions to positive emotions reported in the short and long term under adverse COVID-19 conditions. As predicted, these expectancies proved protective, being associated with positive emotions. Moreover, positive emotions contribute to positive expectancies, demonstrating the reciprocal relationship between these variables.

Positive expectancies as predictors for positive emotions

For optimism, our hypothesis was confirmed. The level of optimism at T1 predicted positive emotions at four months (T3), while it did not predict positive emotions at two weeks after the initial measurement (T2) (when controlling for response hope, response expectancy, and positive emotions at T1), which indicated that optimism was more relevant in the long term. Our result is in accordance with another longitudinal study that illustrated the role of optimism in predicting positive emotional outcomes in the long term (Jovanović et al., 2021). In this study, higher levels of optimism predicted a higher level of life satisfaction a year and a half later. Furthermore, Heinitz and collaborators (2018) showed that optimism predicted life satisfaction and positive affect three years later. With respect to the COVID-19 pandemic, a recent study demonstrated that both optimism and state-positive anticipation predicted an increase in positive emotions during this adverse context (Leslie-Miller et al., 2021). Therefore, our study further supports the robust relationship between optimism and long-term positive emotional experience but also points to the beneficial effects of optimism during the COVID-19 context.

Our hypothesis regarding response expectancy for positive emotions was confirmed. Response expectancy at T1 predicted the experience of positive emotions at T2 but not at T3 (when controlling for response hope, optimism, and positive emotions at T1). Those who expected to experience more positive emotions at T1 reported greater positive emotions two weeks later but not four months later. This result is consistent with the response expectancy theory, which postulates that an individual's anticipation of experiencing particular emotions has a direct effect on those emotions. According to Kirsch (1990), response expectancies are more accurate and have the strongest impact when they are measured prior to and closer to the specific predictions (two weeks) but less accurate and strong in the long term (four months), which explains the nonsignificant association between response expectancy at T1 and positive emotions at T3. Few studies have examined the impact of specific positive expectancies (response expectancy) in determining positive emotions, while generalized positive expectancies (optimism) have been extensively studied.

With respect to response hope for positive emotions, our hypothesis was not confirmed, which means that response hope did not predict positive emotions at T2 or T3 (when controlling for response expectancy, optimism, and positive emotions at T1). While prior research yielded mixed results, with one study indicating a positive correlation between response hope and positive emotions (Cristea et al., 2011), and another showing no association (Anton & David, 2013) our findings further support the idea that response hope may not be particularly relevant in predicting positive emotions, especially when other important variables are taken into account.

Regarding the discrepancy score (Response Hope - Response Expectancy), it negatively predicted positive emotions at T2 but not T3 (when controlling for discrepancy score and positive emotions at T1). In particular, a high discrepancy score (reflecting a high level of hope for experiencing positive emotions but a low expectancy for experiencing them) was associated with decreases in positive emotions at two weeks, confirming our hypotheses that specific expectancies influence the proximal emotional outcome. This result is consistent with previous research (Anton & David, 2013; David et al., 2006) demonstrating that a high discrepancy score for a positive outcome is associated with increased distress and decreases in positive emotions in that specific situation.

Reciprocal influences between variables

In the case of positive emotions, our results showed that the experience of positive emotions at T1 predicted response expectancy, response hope, and optimism at two weeks (when controlling for response hope, response expectancy, and optimism at T1). In other words, experiencing a high level of positive emotions contributed to a more positive outlook in the short term. This result supports the well-known idea that positive emotions expand cognition and increase attention. Similar to our findings, experimental studies evaluating the Broaden-and-Build theory (Fredrickson, 2001) demonstrated that positive emotions increase the levels of optimism (Fredrickson et al., 2008), especially in the short term. With respect to the finding that positive emotions predicted response expectancy and response hope on the short term, to our knowledge, this is the first study to demonstrate this association.

In contrast, we found that the experience of positive emotions at T1 did not predict any positive expectancies (when controlling for each type of expectancy) four months later (in the long term). This result contradicts results obtained by Jovanović and collaborators (2021) who found that greater positive emotions predicted greater levels of optimism six months and two years later. This difference may be partially explained by statistical power and analytical methods. Regarding statistical power, their study had a larger sample size ($N = 367$) compared to the present study. As for the analytical approach, they constrained the autoregressive paths to zero, potentially leading to an increase in the magnitude of the coefficients for the cross-lagged paths. Related to the finding that positive emotions did not predict response expectancy and response hope on the long term, to the best of our knowledge, this is the first study to show this null finding. More studies are needed to further clarify the role of positive emotions in relation to these specific positive expectancies.

With respect to response expectancy, we obtained the following results. First, response expectancy for positive emotions predicted the level of optimism experienced at two weeks and four months (when controlling for response hope, positive emotions, and optimism at T1). In other words, individuals who expected to experience positive emotions in the immediate future showed an increased optimism at two weeks and four months (when controlling for their initial level of optimism), demonstrating the impact of response expectancy on a positive outlook toward the future. The role of response expectancy in relation to optimism was not supported by previous results (Montgomery et al., 2003). Second, response expectancy for positive emotions at T1 predicted response hope at T2 (when controlling for optimism, positive emotions, and response hope at T1) but not at T3. In other words, individuals who expected to experience positive emotions at T1 also reported higher response hope for positive emotions at two weeks. Thus, the observed pattern that response expectancy predicted optimism in both the short and long term but only predicted response hope in the short term, can be partially explained by the nature of these variables. Response expectancy, being a state variable, may have a more immediate and direct impact on other proximal variables, which are measured at two weeks. In contrast, response hope, being a state variable, is more susceptible to fluctuations and may not maintain a consistent relationship with response expectancy over a longer duration (four months). However, even though not on long term, current findings further demonstrate the strong association between response expectancy and response hope on short term.

Thus, we further point toward the beneficial effect of response expectancy for positive emotions as a protective factor relevant to proximal emotional outcomes (positive emotions), positive cognitions (response hope), and a distal positive mindset (optimism) while facing difficult situations.

Regarding response hope for positive emotions, we obtained an interesting and unexpected result regarding optimism. Specifically, response hope at T1 negatively predicted optimism at T2 and T3 (when controlling for response expectancy, positive emotions, and optimism at T1). In other words, endorsing higher levels of response hope for positive emotion at T1 was associated with lower optimism at two weeks and four months. Importantly, this is true only when the other variables are controlled. The zero-order correlations showed significant positive associations between response hope and optimism, in accordance with previous research (Cristea et al., 2011). However, when we controlled for the shared variance of response hope with response expectancy, positive emotions, and optimism (T1), the cross-lagged path between response hope (T1) and optimism (T2) became negative. One possible explanation for this finding is that, in certain cases, increased levels of response hope may have detrimental effects. For example, when hope is overly optimistic, unrealistic, or based on exaggerated positive illusions, it can be challenging to fulfil these hopes. In such instances, when these unrealistically high hopes are not met, they may lead to disappointment or a reduction in optimism. Nevertheless, since this study is the first to suggest the potential detrimental impact of response hope, these findings should be interpreted cautiously. Furthermore, future studies should replicate these findings to clarify whether supporting high response hope during uncertain situations has beneficial or adverse consequences.

Regarding the discrepancy between response hope and response expectancy for positive emotions, the current findings support the direct effect of the discrepancy score on optimism reported in the short term and in the long term in a negative context. To our knowledge, this relationship has not previously been investigated, but it may have important implications. From a clinical perspective, the discrepancy score is relevant. For example, reducing the discrepancy score (by increasing the response expectancy level for positive outcomes) might also impact optimism and positive emotions.

To our knowledge, this is the first study to investigate the reciprocal relationships between specific positive expectancies (such as response expectancy, response hope, and discrepancy score) and positive emotions. The predictive design with multiple measures (T0, T1, T2) and the advanced data analysis procedures allowed us to show the dynamic and reciprocal influences between these variables. Furthermore, we examined these relationships during a stressful context, such as the COVID-19 pandemic. From a theoretical perspective, current findings may enhance our understanding of the interaction between positive expectancies in enhancing and maintaining positive emotions during a stressful period. The findings indicate that response expectancies can predict changes in more general variables (optimism) and proximal positive emotions.

The current findings have practical implications for maintaining and promoting positive affect and expectancies during stressful situation, like COVID-19 pandemic. Public health messaging should incorporate positive expectancies for a resilient response to the crisis. Additionally, clinical practitioners should vigilantly monitor patients' expectancies throughout their treatment. Enhancing response expectancy for positive outcomes is crucial for improving psychological well-being, and addressing unrealistic or unhelpful beliefs about the treatment can significantly impact the patient's progress. Clinicians can use persuasive tactics to highlight the potential benefits of psychotherapy ("CBT offers the latest evidence-based techniques tested in gold standard, controlled clinical trials"), especially at the beginning of treatment (Constantino et al., 2012). Also, educating clients about how the intervention leads to positive changes in psychological mechanisms and outcomes can boost their belief in treatment effectiveness ("Psychotherapy targets cognitions and can be quite effective for helping you feel better."). Not least, providing hope-inspiring statements to the patient's specific situation and positive feedback can further bolster outcome expectations ("I've seen your increased assertiveness in social situations. Great job! I believe you can maintain this progress, which will boost your confidence in social settings.") (Kirsch, 1990).

With respect to response hope our study suggests that promoting response hope should be approached with caution. For example, when hope is overly optimistic, unrealistic, or based on exaggerated positive illusions, it can be challenging to fulfil these hopes. Therefore, one implication of supporting or promoting response hope is the possibility of raising hopes to a level that becomes challenging to attain. This, in turn, may lead to disappointment or a decrease in optimism when these unrealistic hopes are not realized. It is essential for interventions and support measures aimed at enhancing response hope during crises to be carefully designed and monitored. While fostering hope is generally considered beneficial, it is important to strike a balance and ensure that it does not lead to unrealistically high hopes that could potentially reduce optimism.

Despite several promising findings, we are aware of some potential limitations. First, response expectancies were assessed using only one item. While one-item measures proved reliable for unidimensional constructs, future studies should include measures incorporating more items to tap these constructs better. Second, the sample size was relatively small, given the complexity of the statistical analysis. In this regard, replication efforts with larger samples are needed. Another limitation is the convenience sample used, where most participants were white Caucasians, predominantly women, and relatively young. Future studies should investigate the relationship between positive expectations and positive emotions using longitudinal designs with more diverse samples (e.g., more men, older age, diverse ethnicities). Finally, experimental designs with expectancies manipulation can provide valuable insight into their roles.

5. Conclusions

Despite current limitations, our study emphasizes the importance of positive expectancies in predicting the experience of positive emotions in the context of the COVID-19 pandemic. Response expectancy predicted proximal positive emotions (two weeks later - T2), optimism predicted distal positive emotions (four months later - T3), and the discrepancy score (Response Hope - Response Expectancy) negatively predicted positive emotions in the short term (T2). Moreover, our results supported a short-term reciprocal interaction between expectancies and positive emotions. Long-term, however, only optimism affects positive emotions. Therefore, positive expectancies play a significant role in determining and maintaining positive outcomes; interventions that target these expectancies may enhance individuals' functioning in stressful situations.

Study 4: The Impact of Response Expectancy on the Efficacy of the Safe Place Imagery: An Experimental Study

According to Kirsch’s (1985) Response Expectancy Theory, response expectancy involves anticipating a specific outcome or response that an individual predicts in a particular situation. This theory claims that response expectancies have three main characteristics: (1) they independently determine outcomes that are not under voluntary control, (2) they act independently from other psychological mediators, and (3) they have a self-confirming nature. Kirsch (1985) states that *nonvolitional reactions* are "experienced as occurring automatically, without volitional effort." Non-volitional outcomes refer to a range of emotional responses (e.g., relaxation, anxiety) and other subjective experiences (e.g., pain, fatigue, nausea). For example, when we expect to feel relaxation, our expectancies increase the likelihood of actually feeling relaxation in a specific situation.

Numerous studies support the significant role of response expectancies as a psychological mechanism determining nonvolitional outcomes across some major domains, such as placebo effect (e.g., Kirsch, 2013), hypnotic interventions (e.g., Lynn et al., 2023) and various applications such as psychological treatment, medical interventions or pharmacological agents (Kirsch, 2015, 2019; Rutherford et al., 2017). Additional evidence has suggested that response expectancies significant impact emotional experiences, including distress (David et al., 2006; Dilorenzo et al., 2011; Montgomery et al., 2007), public speaking anxiety (Podină & Vîslă, 2014; Vîslă et al., 2013), positive affect (Cristea et al., 2011; Geers & Lassiter, 2002), and relaxation (David et al., 2006). The existing literature focuses on the association between response expectancy and negative emotional outcomes, such as distress and anxiety, in various contexts with negative valence. Thus, response expectancies accurately predict emotions in both cross-sectional and experimental studies (e.g., Podină & Vîslă, 2014; Cristea et al., 2011). Additionally, a meta-analysis conducted by Coteţ and David (2016) identified a moderate to large effect size for the association between response expectancies and negative emotions, and a moderate effect size for the association between response expectancy and positive emotions.

However, few studies have explored the effect of expectancies in experimental studies. In addition, the majority of the experimental studies investigated the relationship between response expectancies and negative emotional outcomes in negative contexts, such as negative mood-induction procedures (e.g., Podină & Vîslă, 2014; Vîslă et al., 2013). In this context, the current study is motivated by two main factors. Firstly, we aim to extend prior investigations by examining the relationship between expectancies and positive emotional outcomes in a positive valence context, such as a positive mood-induction procedure. Secondly, there is a recognized need for more research into experimental paradigms that involve the manipulation of expectancies. This study is significant because it allows for exploring causality in the expectation-emotional experience relationship. Moreover, gaining a deeper understanding of the effects of expectancies on positive emotions could provide insights into the mechanisms underlying these positive experiences, which are less explored in the empirical literature (Pavic et al., 2022).

Thus, in the current study, we focused on investigating the effects of response expectancies on relaxation and positive emotions using a positive mood induction procedure, namely Safe Place Imagery. Specifically, in the current study, we explored whether manipulating the expectancies of individuals related to the efficacy of this positive intervention procedure will impact their experience of positive emotions and relaxation, assessed both at the subjective and physiological levels.

Imagery techniques constitute a primary method for mood induction (Di Pompeo et al., 2023), wherein participants are guided to represent specific mental imagery in their minds. The Safe Place technique, a prevalent form of mental imagery, implies that individuals construct an image of safety and comfort based on guided instructions (Hackmann et al., 2011). Research has shown that Safe Place imagery, as an independent technique, significantly enhances relaxation and positive emotions (Drujan et al., 2023; Seebauer et al., 2014). Moreover, when combined with other methods, it has demonstrated efficacy in increasing positive emotions and reducing stress (Basile et al., 2018; Hackmann et al., 2011; Matos et al., 2022; Prinz et al., 2019; Blackwell, 2021). Additionally, creating a safe place image is an essential component of the initial phase of schema therapy, which has proven effective in managing intense negative emotions (Heath & Startup, 2020; Roediger et al., 2018). This technique has been effectively utilized alone or in conjunction with other methods in both therapeutic and experimental settings (Blackwell, 2021).

Objectives

Thus, the primary aim of this study was to address a gap in understanding the role of response expectancy in influencing the experience of positive emotional outcomes during a positive mood induction technique. More specifically, our goal was to explore whether different expectancies (positive, negative, or no expectancies) for experiencing positive emotions during a mood induction procedure (Safe Place imagery) would lead to differences in positive emotional outcomes (relaxation states and positive emotions). Additionally, we conducted exploratory analyses on the differences between groups regarding physiological markers of emotional responding (Heart Rate (HR), Root Mean Square of Successive Differences (RMSSD), and Skin Conductance Level (SCL)). Considering multiple dimensions in measuring emotions, such as subjective (experiential level) and objective (psychological level) dimensions, is essential for a more comprehensive and nuanced understanding of the effects of expectancies on emotional responses (e.g., Mauss & Robinson, 2010).

2. Methods

The protocol has been registered on the AsPredicted pre-registration platform under the number 118367 (link: https://aspredicted.org/CC9_T82).

2.1. Participants

A total of 191 individuals were recruited through online postings on the social groups of the University between January 2023 and April 2023. Inclusion criteria comprised (a) voluntary agreement to participate in the study and (b) a minimum age of 18. Thirty-one of them later withdrew or failed to schedule the laboratory session. Thus, the final sample comprised 164 participants, 115 females (70.6 %) and 48 males (29.4 %), with a mean age of 22.55 (SD=5.67) and an age range of 18 to 50 years.

2.2. Measures

Positive emotions. We used the Positive Affect (PA) subscale of the Positive and Negative Affect Schedule (PANAS; Watson et al., 1988) to measure positive emotions, focusing on the 10 positives out of 20 mood adjectives for affect. Participants rated their emotions on a 5-point Likert scale, with scores ranging from 10 to 50—higher scores indicating more positive affect. This scale was validated for non-clinical samples (Crawford & Henry, 2004), and our study's PA subscale demonstrated high internal consistency (α = .847–.860).

Relaxation states. Relaxation States Inventory-3 (RSI-3; Smith, 2010) consists of 38 self-report items divided into several subscales, five relaxation categories (basic relaxation, core mindfulness, mindful doing, mindful giving, and deep mindfulness), and three stress states (somatic stress, worry, and negative emotion). Participants were instructed to rate each item by how they feel "right now" on a 6-point Likert scale (1=*not at all*, 6=*maximum*). In the present study, we used only the total score for relaxation states composed of the five categories of relaxations. The Cronbach's alpha coefficient for the total score for relaxation states was high, α =.929.

Physiological markers. We used the Empatica E4 wristband for real-time physiological monitoring, capturing heart rate (HR), heart rate variability (HRV) via Root Mean Square of Successive Differences (RMSSD), and electrodermal activity through Skin Conductance Level (SCL). These measures were recorded continuously during the baseline and intervention phases. HR indicates cardiovascular function, RMSSD reflects the variability in time intervals between successive heartbeats, and SCL measures electrodermal activity (Kreibig, 2010; Shaffer & Ginsberg, 2017). The E4's validity for physiological measurements has been confirmed in controlled, low-movement lab settings (e.g., Stuyck et al., 2022).

Response expectancies. We evaluated participants' expectancies for positive emotions and relaxation, focusing on both expected magnitude and strength, as proposed by Kirsch (2018). The response expectancies for positive emotions were measured using the ten self-report items based on the adjectives from the PA subscale (e.g., interested, excited). In contrast, the response expectancy for relaxation contained a single item, aligning with prior methods (Montgomery & Bovbjerg, 2000). The validity and reliability of single-item measures are supported by previous research (Allen et al., 2022; Ang & Eisend, 2018). The magnitude dimension was assessed using items like "How much relaxation do you expect to feel after the imagery exercise?". In contrast, the strength or certainty dimension was evaluated differently, for example, "How certain are you that you will feel relaxed after the imagery exercise?". Participants responded on an 11-point Likert scale (0=not at all, and 10=to a great extent), where higher scores indicated a higher level of response expectancy for each dimension. Regarding response expectancies for positive emotions, a total score was calculated for the dimensions of magnitude (α=.903) and strength (α=.929), demonstrating a high internal consistency.

2.3. Procedure

Online phase: Participants were recruited via social networks and provided a link with study details, initial consent, and a form to collect demographic and clinical information. The study was approved by the University's Institutional Review Board.

Experimental phase: Eligible participants attended a 40-minute lab session. Before beginning the experiment, all participants received written informed consent, specific details about the procedure, and physiological data acquisition. The experimental phase contained a baseline measure and a mood-induction procedure based on an imagery intervention.

Baseline measures. The initial 5-minute physiological data collection was done with participants seated in front of a laptop, and they were instructed to move as little as possible. At the end of the baseline period, participants completed measures corresponding to T0 (SRSI-3 and PANAS-PA-state). In the subsequent phase, the experimenter provided verbal instructions regarding the efficacy of the Safe Place imagery specific to each experimental condition, complemented by written instructions (see Table 2). After this, participants completed the response expectancies measures corresponding to T1.

Intervention phase. The guidance for Safe Place Imagery was based on the script by Roediger and collaborators (2018), with the same instructions provided for all conditions. The imagery instructions were delivered in an audio format for 14 minutes, during which physiological data were continuously collected. After the imagery intervention, participants completed the last measures corresponding with T2 (SRSI-3 and PANAS-PA-state). At the end of the experimental session, the experimenter conducted a short debriefing for participants from the Negative Condition regarding the purpose and the experience.

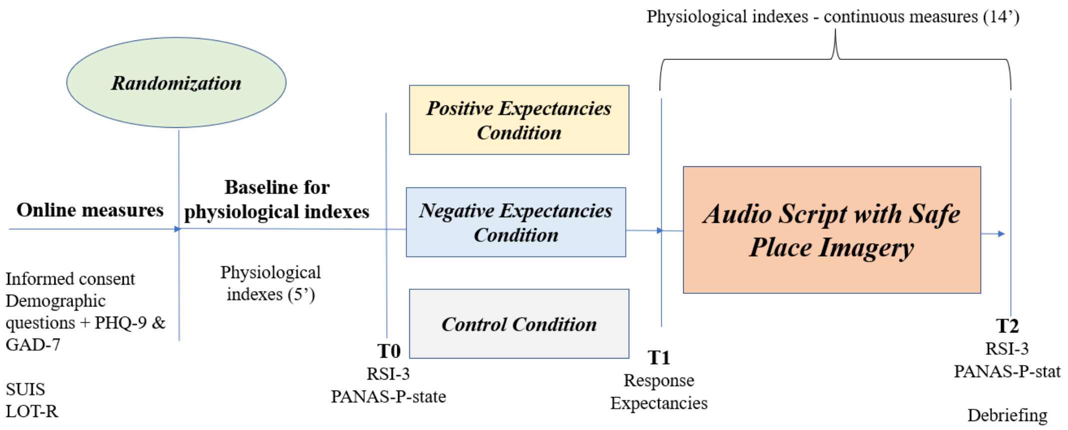

Figure 1: Data Collection Process and Associated Measurement

Expectancies were manipulated by verbal and written instructions, which were specific to each experimental condition: (1) Positive Condition (positive expectancies in the direction of the imagery effect), (2) Negative Condition (negative expectancies in the opposite direction of the imagery effect, and (3) Control Condition (expectancies were not manipulated).

2.4. Preprocessing of psychophysiological data

BVP raw data were preprocessed in MATLAB to extract the IBI time series and correct, upon visual inspection, ectopic and wrongly detected peaks. Starting from the artifact-free IBI time-series we derived the cardiovascular measures of interest, namely heart rate (HR) and the root mean square of successive differences (RMSSD). EDA raw data were preprocessed in MATLAB using the Continuous Decomposition Analysis implemented in the LedaLab toolbox (Benedek & Kaernback, 2010) to estimate changes in the tonic skin conductance level (SCL) during the task.

2.5. Data analysis plan

To analyze the primary data, we utilized two multivariate ANCOVAs (MANCOVAs) and one univariate ANCOVA with a 3-group experimental design (Positive Condition, Negative Condition, and Control Condition) to evaluate the effect of the group on non-volitional outcomes (positive emotional outcomes, cardiovascular markers – HR and RMSSD, and SCL analysed independently), using the baseline scores as covariates. The first MANCOVA aimed to identify statistically significant differences in positive emotional outcomes (relaxation states and positive emotions) post-induction between the positive, negative, and control expectancy groups while controlling for pre-induction levels of relaxation and positive emotions. The second MANCOVA sought to determine statistically significant differences in cardiovascular physiological outcomes (HR and RMSSD) during induction among the positive, negative, and control expectancy groups while controlling for pre-induction/baseline levels of HR and RMSSD. In the case of the univariate ANCOVA, the analysis sought to determine statistically significant differences in SCL during induction among the positive, negative, and control expectancy groups while controlling for pre-induction/baseline levels of SCL. Analyses were conducted in SPSS and JASP.

1. Results

Manipulation check

No significant differences in baseline characteristics were observed among the three conditions, indicating successful randomization. Furthermore, results showed significant differences across the three groups in terms of expectancies. In the case of response expectancy for positive emotions, results indicated a significant effect of Condition for Expected Magnitude [$F(2, 160) = 7.30$, $p < .001$, $\eta 2 = 0.08$], and Expected Strength [$F(2, 160) = 6.59$, $p < .05$, $\eta 2 = 0.07$]. Pairwise comparisons (Sidak corrected) performed on the main effect of the Group revealed that the Positive Condition reported significantly more response expectancy for positive emotions than the Negative Condition (Expected Magnitude: mean difference = 8.59, SE = 3.04, $p < .05$, and Expected Strength: mean difference = 9.68, SE = 3.58, $p < .05$). In contrast, the Control Condition reported significantly more response expectancy for positive emotions than the Negative Condition (Expected Magnitude: mean difference = 11.37, SE = 3.12, $p < .001$, and Expected Strength: mean difference = 12.73, SE = 3.69, $p < .05$). For response expectancy for relaxation, results indicated a significant effect of Condition for Expected Magnitude [$F(2, 160) = 13.96$, $p < .001$, $\eta 2 = 0.14$] and Expected Strength [$F(2, 160) = 16.51$, $p < .001$, $\eta 2 = .17$]. Pairwise comparisons (Sidak corrected) performed on the main effect of the Group revealed that the Positive Condition reported significantly more response expectancy for relaxation than the Negative Condition (Expected Magnitude: mean difference = 1.33, SE = .29, $p < .001$, and Expected Strength: mean difference = 2.04, SE = .39, $p < .001$). In contrast, the Control Condition reported significantly more response expectancy for relaxation than the Negative Condition (Expected Magnitude: mean difference = 1.41, SE = .30, $p < .001$, and Expected Strength: mean difference = 1.91, SE = .40, $p < .001$). These results suggest that manipulating individuals' response expectancies was effective in the current study.

Table 3. Means and standard deviations for emotional and physiological outcomes and expectancies variables

Variables	Positive Condition (n= 57)				Negative Condition (n= 55)				Control Condition (n= 51)			
	Baseline		Induction		Baseline		Induction		Baseline		Induction	
	m	*SD*	*m*	*SD*	*m*	*SD*	*m*	*SD*	*m*	*SD*	*m*	*SD*
Positive Emotions	31.96	7.37	35.07	7.75	31.25	6.35	31.36	7.97	32.62	7.49	34.84	7.66
Relaxation States	102.35	20.52	127.29	20.80	96.89	19.79	114.54	22.37	102.35	25.51	124.74	24.97
Heart Rate	88.51	13.03	85.10	12.36	93.07	11.99	88.17	10.05	88.06	11.98	85.75	12.38
RMSSD	64.36	25.93	68.77	42.48	68.07	45.38	70.03	51.66	70.45	37.59	75.78	47.36
Skin Conductance Level	1.16	2.42	1.01	1.45	1.05	1.33	.61	.62	.96	1.30	.43	.38
Variables measured only once (M, SD)												
RE magnitude for Relaxation	7.89 (1.27)				6.56 (1.89)				7.98 (1.47)			
RE strength for Relaxation	7.64 (2.04)				5.60 (2.33)				7.51 (1.84)			
RE magnitude for Positive Emotions	68.10 (13.90)				59.50 (17.44)				70.88 (16.85)			
RE strength for Positive Emotions	70.28 (19.14)				60.60 (18.79)				73.33 (19.03)			

Notes: RMSSD = Root Mean Square of Successive Differences; RE = Response expectancy

Main Analyses – Imagery Efficacy

The effects of Safe Place Imagery on positive emotional outcomes

A Multivariate MANCOVA investigated the differences between the three groups (Positive Condition vs Negative Condition vs Control Condition) regarding positive emotional outcomes. The multivariate was statistically significant, Wilks' Lambda = .92, F (4, 314) = 3.09, $p < .05$. Further, univariate analyses indicated a statistically significant effect for relaxation states, F (2, 158) = 4.11, $p < .05$., $\eta 2$ p = .05, respectively for positive emotions, F (2, 158) = 5.58, $p < .05$, $\eta 2$ p = .06. Post-hoc Sidak adjusted pairwise comparisons revealed that the participants in the Positive Group had statistically significant higher scores than the Negative Condition for relaxation states (Positive Condition vs. Negative Condition, mean differences = 9.109, $p < .05$) and positive emotions (Positive Condition vs. Negative Condition, mean differences = 3.11, $p < .05$; and marginally significant between Control Condition vs. Negative Condition, mean differences = 2.33, $p = .059$). Thus, the participants in the Positive Condition had statistically significantly higher scores post-induction than those in the Negative Condition for relaxation states and positive emotions when controlling for pre-induction levels of relaxation and positive emotions.

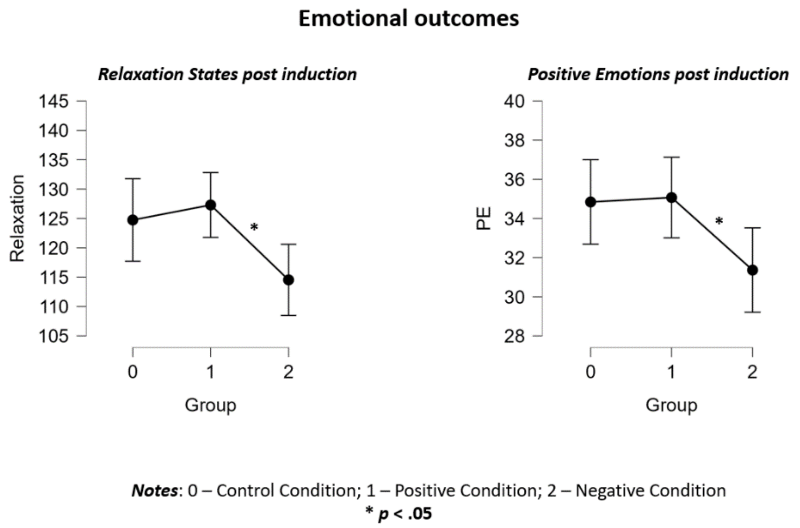

Figure 2. Graphical representation for the three conditions regarding emotional outcomes reported at post-induction.

The effects of Safe Place Imagery on physiological markers

In examining continuous physiological markers, we compared baseline measures (a mean score for the 5 minutes of baseline) with physiological measures during the imagery induction (a mean score for the 14 minutes of the imagery exercise). In this sense, we conducted a MANCOVA for correlated variables (HR and RMSSD) and an ANCOVA for SCL. Concerning the MANCOVA, the between-subjects main effect (group effect: Positive Condition vs Negative Condition vs Control Condition) was statistically non-significant, Wilks' Lambda = .99, F (4, 314) = .296, p = .881. Thus, response expectancies do not have an observed effect on HR and RMSSD. An ANCOVA analysis was conducted to investigate the differences between the three groups regarding SCL during imagery when the baseline level was controlled. The group effect was statistically significant, F (2, 163) = 3.48, p < .05., η2 p = .04. Post-hoc Sidak adjusted pairwise comparisons revealed that the participants in the Positive Group had statistically significant higher scores during induction than Control Condition for SCL level (Positive Condition vs. Control Condition, mean differences = .308, p < .05).

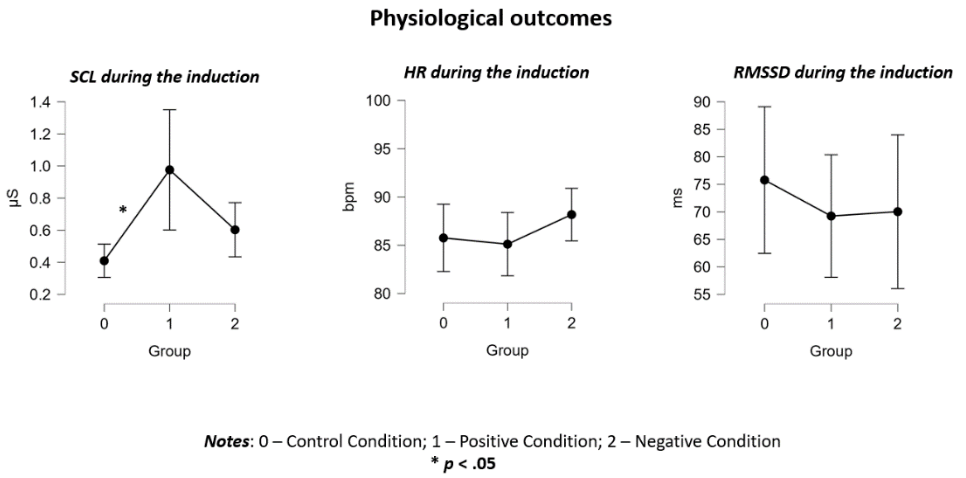

Figure 3. Graphical representation for the three conditions regarding physiological outcomes during the induction procedure.

Discussion

The primary goal of our study was to address the knowledge gap concerning how response expectancy influences non-volitional outcomes after a positive mood induction in a laboratory context. Specifically, we explored whether providing positive, negative, or no expectancies regarding the efficacy of Safe Place imagery would lead to differences in positive emotional outcomes (relaxation states and positive emotions) and variations in physiological markers (HR, RMSSD, and SCL).

Response Expectancies and Positive Emotional Outcomes

The results partially support our hypothesis regarding the effects of response expectancies on positive emotional outcomes (relaxation states and positive emotions). Specifically, when the levels of positive emotional outcomes at pre-induction were controlled, individuals in the Positive Condition reported significantly higher levels of relaxation and positive emotions after the induction than those in the Negative Condition. However, no significant differences were observed between individuals in the Positive and Negative Conditions and those in the Control Condition. This finding suggests that having explicit and well-defined expectancies in valance (positive or negative) can significantly influence the experience of positive emotional outcomes after a positive mood induction procedure. For example, holding positive expectancies about the effects of Safe Place Imagery can enhance the efficacy of the technique and produce beneficial outcomes (increase levels of positive emotions and relaxation). Conversely, holding negative expectancies can diminish the effectiveness and lessen the positive impact.

Our findings align with Kirsch's (1985) response expectancy theory, which posits that individuals' emotional experiences and reactions are shaped by their expectations. Also, Coteţ and David (2016), through their meta-analysis of correlational studies, found that individuals are generally accurate in predicting positive emotions. Moreover, several experimental and clinical studies have documented the causal role of response expectancy (via expectancy manipulation) in influencing negative emotions, such as depression, anxiety, and social anxiety (Colloca et al., 2004; Rutherford et al., 2016; Baldwin et al., 2016). However, research on manipulating expectancies related to positive emotions is markedly limited.

Preliminary evidence comes from a prior line of research demonstrating the impact of expectancies on the outcomes of placebo psychological interventions (Helfer et al., 2015; Kwan et al., 2017; Mothes et al., 2017; Wang et al., 2020). Positive expectancies regarding a placebo intervention, such as engaging in physical exercise, lead to positive mood or perceived benefits both during and after exercise. Conversely, negative expectancies are more likely to result in negative mood or perceived adverse effects following exercise (Helfer et al., 2015; Kwan et al., 2017; Mothes et al., 2017). A recent study conducted by Wang and colleagues (2020) explored the impact of expectancies (positive, negative, and neutral) on affective responses during and after a 30-minute moderate-intensity aerobic session. The findings revealed that individuals with positive expectations (such as anticipating feeling good, energized, more active, and relaxed post-exercise) tended to report positive mood and beneficial effects during and after the session. Conversely, those with negative expectations (expecting to feel worse, tired, less active, and less relaxed) experienced heightened perceived physical exertion, a nocebo effect. Our study extends this previous line of research in which the role of expectancies was investigated in relation to placebo psychological interventions, focusing on positive emotional outcomes in the context of active psychological intervention (Safe Place Imagery). Our approach allows us to investigate the interaction between response expectancies and the active treatment ingredient in determining positive emotions. Concerning the medical context and pharmacological treatments, the interplay between expectancies and the efficacy of active treatments has been studied (e.g., Peerdeman et al., 2016). For example, Faria et al. (2017) found that individuals who received overt escitalopram (SSRI treatment combined with positive expectations) reported a significant reduction in social anxiety symptoms compared to those who received escitalopram in the covert condition (SSRI treatment without explicitly defined expectations). Our findings are consistent with their research, underscoring the significant influence of positive expectations on the effectiveness of treatments that contain active ingredients. Furthermore, our study suggests that negative expectancies might diminish the efficacy of active treatments, supporting previous findings related to the analgesic effects in pain management (e.g., Kube et al., 2020; Vase & Wartolowska, 2019). In their systematic review, Peerdeman et al. (2016) demonstrated that modulating expectancies about pain reduction could alleviate pain and improve functionality. Medium to large effects were observed for experimentally induced pain and acute procedural pain, while smaller effects were noted for chronic pain conditions. Therefore, positive expectancies can enhance treatment outcomes, whereas negative expectancies may undermine the effectiveness of interventions.

To our knowledge, only one previous study has explored the influence of response expectancies on positive emotions within the context of positive mood induction. Geers and Lassiter (2002) conducted a laboratory study to assess how optimism-pessimism moderates the relationship between expectancies and positive emotional outcomes. Their findings indicated that pessimistic individuals, regardless of having positive or negative expectations for the same funny film clip, experienced higher levels of positive affect. Conversely, optimistic individuals with negative expectations for the same clip experienced lower levels of positive affect and enjoyed the experience less compared to their pessimistic counterparts (Geers & Lassiter, 2002). In contrast to Geers and Lassiter (2002), our study examined how different expectancies (positive, negative, and no expectancies) determine non-volitional responses following a positive mood induction procedure. The relevance of the current research lies in its potential to examine causality within the expectation-experience relationship, providing a deeper understanding of the underlying mechanisms involved in positive emotional experiences. Moreover, Kirsch (1990) suggested that response expectancies have a stronger impact and are more accurate when assessed both before and in close temporal proximity to the specific expected response.

Response Expectancies and Physiological Outcomes

Our results provide interesting insights into the differential impact of positive, negative, and no expectancies on physiological outcomes, such as SCL. Individuals in the Positive Condition showed higher SCL levels than those in the Control Condition after controlling for baseline level. SCL is often associated with emotional and physiological arousal (Braithwaite et al., 2013), suggesting that positive expectancies could significantly influence arousal levels. Our finding is particularly relevant for relaxation-promoting interventions, indicating that positive expectancies toward a positive technique might amplify physiological indicators of emotional engagement or arousal.

In the case of HR and RMSSD, our results showed no significant differences across conditions during the induction phase after controlling for baseline levels. This result contrasts with the findings of Wang et al. (2020), who observed an effect of expectancies on RMSSD during aerobic exercise. However, their results only demonstrated a time effect when analysing RMSSD post-exercise. They explored the influence of response expectancy on the outcomes of 30-minute moderate-intensity aerobic exercise sessions. A potential reason for the differences between our results and theirs could be that HR and RMSSD, indicators of the autonomic nervous system's regulation of the heart, are more sensitive to psychological manipulations during longer durations of activity or intervention (exceeding 15 minutes) or under specific movement conditions. Future studies are needed before drawing any conclusive conclusion.

Limitations and Future Directions

The study's findings should be interpreted within the context of several limitations. Firstly, the study used convenience sampling to recruit participants through social media and university groups. Most of the participants were healthy individuals from a collectivistic society, exhibiting high levels of well-being, which may restrict the generalizability of the findings. Furthermore, the majority of our sample were women. Future studies should replicate these findings with a gender-balance population, considering different cultural and sociodemographic backgrounds and clinical statuses. Another critical limitation involves the using a single item to assess response expectancies concerning relaxation. Although one-item measures have demonstrated reliability in assessing unidimensional constructs (Allen et al., 2022; Ang & Eisend, 2018), future research should utilize measures encompassing a broader range of items to evaluate this construct more effectively. Finally, we focused on the influence of response expectancies for overall positive emotions, calculating a total score rather than examining each positive emotion individually. In this regard, an important direction for future research involves exploring how accurately response expectancies influence different positive emotions, distinguishing between those with low and high arousal levels. Comparative studies on positive emotions across different arousal levels are crucial for a deeper understanding of the role of response expectancy in positive emotionality (Kraiss et al., 2023; McManus et al., 2019). Additionally, as the body of research examining the relationship between expectations and positive emotions expands, there is also the possibility of comparing the accuracy of response expectancies based on emotional valence, respectively, and arousal level. For instance, it would be pertinent to examine the accuracy of response expectancies in predicting emotions characterized by low arousal levels (such as relaxation, for positive emotions, and sadness, for negative emotions) compared to those characterized by high arousal levels (such as joy, for positive emotions, and fear, for negative emotions). Another important research direction is exploring dispositional traits as moderators in the dynamics between response expectancy and emotional outcomes. It would be particularly relevant to investigate if the influence of response expectancy on emotions differs under specific variability in dispositional variables. For instance, future research should examine whether having different levels of emotional awareness leads to different levels of accuracy between response expectancies and emotional outcomes.

Despite the previously mentioned limitations, the current results provide some important contributions. From a theoretical perspective, our findings demonstrate that response expectancy for positive emotions accurately predicts positive emotional outcomes. Moreover, our data suggest that response expectancy substantially impacts emotional outcomes when they are clearly defined in valence. For instance, positive response expectancy can enhance positive emotions, while negative response expectancy can diminish positive emotions in a particular situation. From a clinical perspective, our results indicate that response expectancy can either maximize (positive response expectancy) or minimize (negative response expectancy) the effectiveness of the active component in positive intervention techniques, specifically the Safe Place Imagery Technique. These results underscore the importance of addressing and correcting negative expectancies during the psychological intervention process to achieve better results. Additionally, our study contributes significantly to understanding expectancies by directly manipulating them in a specific context. This method is vital because individuals frequently do not independently form their expectations. The phenomenon reflects real-life circumstances in which individuals' expectancies are shaped or influenced by a variety of sources, including friends, acquaintances, or authoritative figures like healthcare professionals or specialists in particular domains, to individuals.

Conclusions

Our study aimed to bridge the knowledge gap in understanding the impact of response expectancy on non-volitional outcomes within an experimental paradigm. We explored the effects of different expectancies (positive, negative, or no explicit expectancies) related to a positive mood-induction technique, Safe Place imagery, on emotional outcomes and physiological markers. For positive emotional outcomes, when controlling for pre-induction levels (positive emotions and relaxation), individuals with positive expectancies exhibited significantly higher levels of relaxation and positive emotions post-induction compared to those with negative expectancies. No significant differences were found between individuals with positive and negative expectancies compared to those with no manipulated expectancies, suggesting that only clear and well-defined expectancies significantly influence emotional outcomes. When considering physiological levels, results showed that individuals with positive expectancies had higher SCL levels than those without manipulated expectancies, indicating that positive expectancies may enhance arousal more than non-manipulated expectations. However, no significant differences were observed in HR and RMSSD across different expectancies, underlining the complex effects of expectancies on physiological responses. Thus, current findings demonstrate that response expectancies substantially impact subjective emotional experiences (positive emotions and relaxation) and some physiological markers, such as SCL, but not for HR and RMSSD.

Study 5: The Impact of Response Expectancy on the Efficacy of the Counting Blessings Intervention: Examining the Moderating Role of Optimism

Introduction

Gratitude interventions refer to deliberate practices or exercises to cultivate and enhance feelings of gratitude. Among these, the "Three Good Things" (TGT) list is one of the most widely used strategies. This exercise asks participants to reflect, write about, and explain three good things that occurred during the day and for which they felt grateful (Emmons & McCullough, 2003). Research suggests that this simple and quick activity has various positive outcomes, including increased positive affect, happiness, life satisfaction, well-being, improved pro-social behavior, better sleep, and enhanced concentration (Chopik et al., 2019; Cunha et al., 2019; Salces-Cubero et al., 2019; Yang et al., 2018). Moreover, the TGT list effectively reduces negative affect, depressive symptoms, and loneliness (Bartlett & Arpin, 2019; Dickens, 2019; Salces-Cubero et al., 2019; Southwell, 2012; Yang et al., 2018). While these outcomes are promising, a knowledge gap exists regarding the mechanisms through which gratitude interventions contribute to promoting of well-being. Recent studies have increasingly focused on exploring potential mediator factors that contribute to the effectiveness of gratitude interventions.

The hypothesis that expectancies might be responsible for positive effects in the case of gratitude interventions is not new. Geraghty (2010) conducted a series of studies investigating the role of response expectancy in a gratitude strategy that yielded favorable results. Notably, he illustrated that greater response expectancy for positive affect was directly related to reports of both greater positive affect and less negative affect. Moreover, more and more results have accumulated, arguing that the well-being improvements associated with gratitude interventions may result from this specific process, response expectancy (Davis et al., 2016; Wood et al., 2010). In this regard, Jans-Beken and collab. (2020), exploring various gratitude interventions, concluded that delivering distinct instructions to participants— manipulating response expectancies during the same exercise— can yield different outcomes. Therefore, modifying expectations about an intervention not only serves as a way to explore potential mechanisms behind changes in outcomes but also provides an opportunity to optimize interventions. In this context, understanding whether intervention instructions (i.e., manipulating response expectancy) impact the effectiveness of gratitude interventions is a critical direction for further research (Cregg & Cheavens, 2021). Building upon these results, we propose to enhance our understanding of the extent to which response expectancy is indeed the mechanism of change in gratitude techniques and its impact on positive outcomes.

According to Kirsch and Lynn (1999), response expectancies are defined as "anticipations of automatic subjective and behavioral responses to particular situational cues, and their effects are a form of self-fulfilling prophecy" (p. 504). Response expectancies are deemed sufficient to determine a nonvolitional outcome, not mediated by other psychological factors, and are self-confirming (Kirsch, 1985). Numerous studies have underscored the significance of response expectancies as a psychological mechanism involved in generating nonvolitional outcomes across various contexts, including psychological treatment, medical interventions, pharmacological agents and placebo effects (Kirsch, 2019; Kirsch et al., 2015; Kirsch et al., 2014; Rutherford et al., 2017).

Kirsch (2018) proposed that response expectancies encompass at least two dimensions: the expected magnitude and the strength of the expectancy, with both dimensions rarely being assessed simultaneously in research. The strength of the expectancy relates to the subjective probability of a change occurring, while the expected magnitude pertains to the intensity or size of the expected outcome (Kirsch, 1985). Furthermore, Kirsch (2018) claimed that response expectancies are fluid and can change in response to new experiences, which evidences the importance of measuring them several times in the same study. Moreover, research has indicated that response expectancies and optimism-pessimism disposition interact in shaping emotional reactions (Geers et al., 2005, 2007; Geers & Lassiter, 2002; Kern et al., 2020). According to this interactionist perspective, optimism-pessimism is a significant moderator for the relationship between response expectancies and affective experiences.

Objectives

The main objective of this research was to address a significant gap in the understanding of gratitude intervention efficacy by studying the role of response expectancy within the context of a randomized controlled trial (RCT). Specifically, we aimed to investigate whether different instructions (positive, negative, or ambiguous) for a gratitude journal led to differences in emotional outcomes (positive and negative emotions).

The secondary objective of this research was to examine the interaction between optimism levels (low, medium, and high) and specific expectations (positive, negative, and ambiguous) about the efficacy of gratitude journals.

Ultimately, we propose to explore the interplay between levels of optimism and the various facets of response expectancies, encompassing both expected magnitude and strength expectancy for positive and negative emotions, assessed at two distinct time points (response expectancies from Day 1 and response expectancies from Days 2 to 7).

3. Methods

3.1. Participants

Inclusion criteria required participants to be (a) aged 18 or older and (b) possess a smartphone with regular internet access to enable completion of the intervention. Eligible participants were automatically assigned to one of three conditions using a Random Sequence Generator. A total of 529 adult volunteers were recruited via social media between June and August 2020. The sample consisted of 462 females (87.3%) and 67 males (12.7%), with an age range of 18 to 63 years (M = 25.44, SD = 8.36).

Out of the initial 529 participants who enrolled at T1, only 151 participants (28.54%) actively engaged in the "counting blessings" intervention over the seven days. Subsequently, only 142 participants (26.84%) proceeded to complete the post-intervention measures at T2. Finally, 111 participants (20.98%) completed the follow-up assessment (T3).

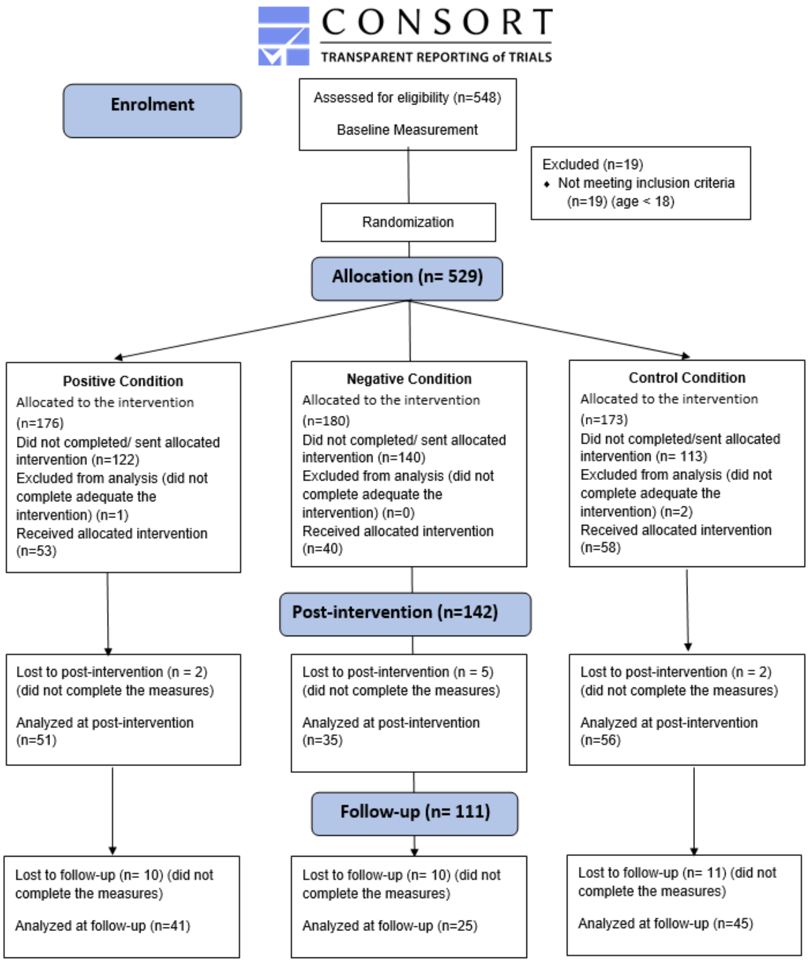

Figure 1: Study Recruiting Method and Data Collection Flowchart

3.2. Measures

Positive and negative emotions. This study employed the Positive Affect and Negative Affect Schedules (PANAS, Watson et al., 1988) to assess emotions. The scale comprises 20 self-report mood adjectives, divided into two categories: half of the items measure positive affect (PA), and the remaining half measure negative affect (NA). The both subscales used in the present study demonstrated good internal consistency.

Response expectancies. In this study, participants' response expectancies were assessed using a single item for each dimension (expected magnitude and strength of the expected) regarding anticipated positive and negative emotions, referring to a specific time when the outcome will occur (e.g., after experiencing this technique - Day 1 – Day 7). The magnitude of the expected response was evaluated with the question (e.g., "How many positive emotions do you expect to feel after this technique?"), while the strength or certainty dimension was assessed differently ("How certain are you that you will feel positive emotion after this technique?"). Participants responded on a 5-point Likert scale (1 = not at all, 5 = to a great extent), where higher scores indicated a higher level of response expectancy for each dimension. It is worth noting that research has demonstrated that single-item measurements are valid, reliable, and appropriate for unidimensional constructs (Allen et al., 2022).

Optimism. The Life Orientation Test-Revised (LOT-R, Scheier et al., 1994) was employed to assess dispositional optimism. Expanding on the existing research that views optimism as a unidimensional construct (Cano-García et al., 2015; Hinz et al., 2021), we propose to explore this disposition on three different levels (high, medium, and low levels of optimism) to offer a more nuanced perspective.

3.3. Procedure and Study conditions

The expectancies were manipulated by written instructions provided before the completion of each electronic journal, corresponding to each experimental condition: (1) positive expectancies (inducing expectations in the direction of the intervention effect - Group 1), (2) negative expectancies (inducing expectations in the opposite direction of the intervention effect - Group 2), and (3) ambiguous expectations (where the direction of the intervention effect was not manipulated - Group 3). We refer to the last condition as the control condition.

The gratitude intervention in this study was based on the 'Three Good Things' list developed by Emmons and McCullough (2003) and Emmons and Stern (2013), with identical instructions provided for all conditions. The intervention was delivered for seven consecutive evenings, with an automatic notification. Each survey included (a) manipulation instructions depending on the condition (see Table 2), (b) questions about response expectancies, and (c) the "counting blessings" technique (see Table 2). The day after concluding the intervention (when the PIEL Survey with the gratitude journal was sent), participants received an email containing a link to complete the post-intervention measures (T2). Follow-up measures were collected a month later (T3).

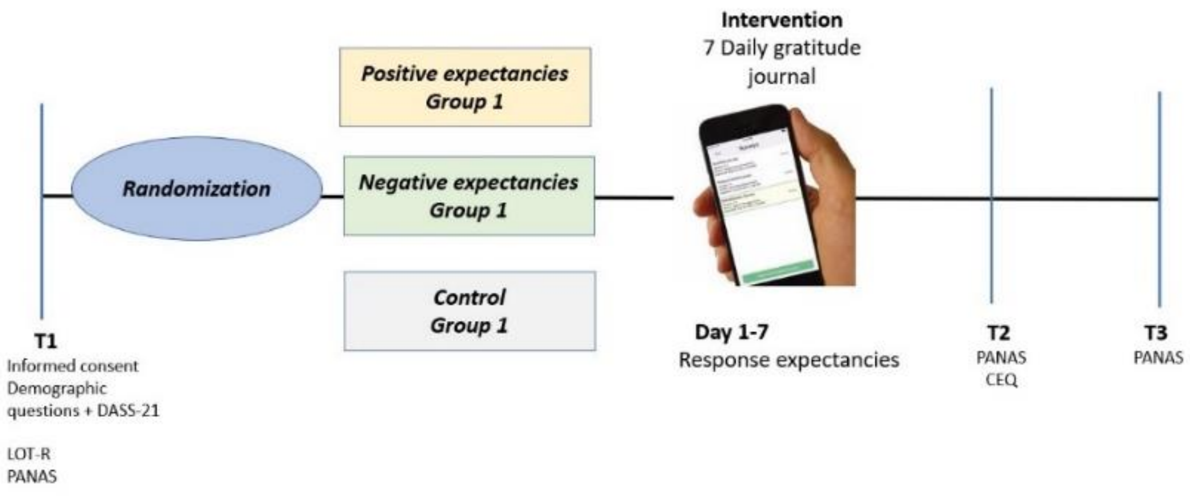

Figure 2. Procedure

3.4. Data analysis plan

Descriptive statistics were computed, plotted, and visualized in SPSS (George & Mallery, 2019). Hypotheses were tested, implying linear mixed models (with random intercepts) in RStudio (RStudio Team, 2019). As for the three measurements (T1, before intervention; T2, after the intervention; T3; follow up), the percentage of missing data was high; we used multiple imputations (Buuren & Groothuis-Oudshoorn, 2011). We considered missing data for those who did not send us the intervention journal survey or did not adequately complete the intervention (see **Figure 1**). Specifically, all the parameters were computed across 100 imputed datasets. For daily measurements, we used all available cases as per implemented in mixed linear models (Hedeker & Gibbons, 1997). The main R packages used were 'mitml' (Grund et al., 2023) and 'lme4' (Bates et al., 2023). We also assessed the moderator role of optimism in the relationship between group and emotional outcomes. Where the three-way interaction effect (group * time * optimism) was found significant, we further assessed the condition * time interaction for different levels of optimism. Specifically, as it is a convention, we split the participants into three groups based on their level of optimism. The low optimism group was composed of those with levels one standard deviation below the mean, and the average optimism group was composed of those with levels of optimism between -1 and 1 standard deviation. Finally, the high optimism group was made up of those who had higher than one standard deviation above the mean. All post hoc analyses were conducted, controlling for type I errors with the false discovery rate method (Benjamini & Hochberg, 1995).

4. Results

4.1. Manipulation check

No statistically significant differences concerning baseline characteristics emerged between the three groups, indicating successful randomization. However, results revealed that the manipulating expectancies was effective in the current study.

4.2. Main analysis - Intervention Efficacy

Positive emotions

No significant main effect existed for the *group* for positive emotions, F (2, 694) = .20, p = .813. However, a significant main effect of *time* was found, F (2, 302) = 16.17, and $p < .001$. Finally, no significant *interaction* between condition and time was found, F (4, 301) = .27 and p = .893.

Negative emotions

No significant main effect existed for the *group* for negative emotions, F (2, 691) = 1.48, p = .227. A significant main effect existed for the *time*, F (2, 296) = 32.14, and $p < .001$. Finally, no significant *interaction* between condition and time existed for negative emotions, F (4, 295) = .143, p = .965.

Descriptive statistics for positive and negative emotions are presented in **Table 3.**

4.3. Secondary analysis - Moderation Analyses

Positive emotions

We found a significant time * group * optimism interaction, with t = -2.64 and $p < .009$.

In the case of low optimism, pairwise comparisons at different moments indicated a significant within-subjects effect (post-intervention vs. follow-up) for Positive Condition (t = -2.42, $p < .016$), respectively, a significant within-subjects effect (pre-intervention vs. post-intervention) for Negative Condition (t = 2.41, $p < .018$). However, no more significant within-subjects effects (pre-intervention vs. post-intervention, pre-intervention vs. follow-up, and post-intervention vs. follow-up) were found for each condition. Pairwise comparisons revealed that participants with a low optimism from all three conditions did not significantly differ regarding positive emotions at pre-intervention, post-intervention, or follow-up (p_s >.05).

In the case of medium optimism, pairwise comparisons at a different moment indicated a significant within-subjects effect (pre-intervention vs. follow-up (t = 3.73, $p < .001$) and post-intervention vs. follow-up (t = 3.28, $p < .001$)) for Positive Condition, a significant within-subjects effect (pre-intervention vs. follow-up (t = 3.39, p =.001), and post-intervention vs. follow-up, (t = 3.43, p = .001)) for Negative Condition, respectively a significant within-subjects effects (pre-intervention vs. follow-up, (t = 3.74, $p < .001$), and post-intervention vs. follow-up, (t = 2.59, $p < .01$)) for Control Condition. However, for each condition, no significant differences were found between pre-intervention vs. post-intervention (p > .05). Pairwise comparisons revealed that participants with a medium optimism from all three conditions did not significantly differ regarding positive emotions at pre-intervention, post-intervention, or follow-up (p_s >.05).

In the case of high optimism, pairwise comparisons at different moments indicated a significant within-subjects effect (pre-intervention vs. follow-up (t = 2.09, p < .038), and post-intervention vs. follow-up (t = 3.06, p < .003)) for Positive Condition, a significant within-subjects effect (pre-intervention vs. post-intervention, (t = -2.76, p < .006), and post-intervention vs. follow-up (t = 2.74, p < .007)) for Control Condition. However, no more significant effects on the within-subjects were found for each condition. Pairwise comparisons revealed that participants with a high optimism from all three conditions did not significantly differ between them regarding positive emotions at pre-intervention and post-intervention (p_s>.05).

Table 3. Means and standard deviations for positive and negative emotions

Variables	**Positive Condition (n=41)**						**Negative Condition (n=25)**						**Control Condition (n=45)**					
	Pre		***Post***		***Follow-up***		***Pre***		***Post***		***Follow-up***		***Pre***		***Post***		***Follow-up***	
	m	*SD*	*m*	*SD*	*m*	*SD*	*m*	*SD*	*m*	*SD*	*m*	*SD*	*m*	*SD*	*m*	*SD*	*m*	*SD*
Positive Emotions	28.48	8.36	29.19	6.04	31.46	8.91	28.27	7.95	30.05	5.76	32.60	7.40	28.97	8.31	29.71	6.17	33.73	8.15
Negative Emotions	28.03	8.79	23.47	5.83	23.65	8.24	26.86	8.38	22.60	4.60	21.52	6.81	26.62	9.50	22.92	5.10	22.35	8.07

Table 4. Optimism as moderator and positive emotions as outcome

	Optimism			**Positive emotions at T1**			**Positive emotions at T2**			**Positive emotions at T3**		
	N	*m*	*SD*	*N*	*m*	*SD*	*N*	*m*	*SD*	*N*	*m*	*SD*
					Positive Condition							
High optimism	30	20.80	1.58	30	35.30	8.07	5	37.00	6.04	4	44.50	7.18
Medium optimism	113	13.61	2.77	113	28.08	7.67	35	28.66	5.94	27	33.07	6.31
Low optimism	34	5.29	2.38	34	23.82	7.00	10	27.10	3.69	10	21.90	5.97
					Negative Condition							
High optimism	25	20.64	1.52	25	33.52	8.89	6	34.17	6.64	5	35.80	9.06
Medium optimism	134	13.91	2.85	134	28.17	7.19	28	28.93	5.18	19	32.79	5.53
Low optimism	21	5.28	2.28	21	22.61	7.75	1	37.00	-	1	13.00	-
					Control Condition							
High optimism	34	20.68	1.60	34	33.91	6.49	14	31.79	4.33	11	36.55	4.43
Medium optimism	107	13.26	2.85	107	29.00	7.90	32	30.47	5.77	27	33.78	8.10
Low optimism	32	5.40	2.74	32	23.65	8.30	10	24.40	7.13	7	29.14	11.43

Negative emotions

We did not find a significant time * group * optimism interaction, with t = 1.50 and p = .136.

4.4. Exploratory analysis - *Expected Magnitude and Strength*

Positive emotions

Regarding the response expectancies evolution and positive emotions as outcomes, we ran two linear mixed models with random intercepts during the daily measure for the three conditions. We focused on each sub-dimension of response expectancy: Expected Magnitude for Positive Emotions and Expected Strength for Positive Emotions.

Expected Magnitude for Positive Emotions

Regarding positive emotions as the outcome, no significant interaction effect was found between group * time * optimism for Expected Magnitude for Positive Emotions, where F (12; 776) = 1.29 and p = .213.

Expected Strength for Positive Emotions

Regarding positive emotions as the outcome, no significant interaction effect was found between group * time * optimism for Expected Strength for Positive Emotions, where F (12; 776) = .39 and p = .965.

Negative emotions

Regarding the evolution of response expectancies and negative emotions as outcomes, we ran another two linear mixed models with random intercepts during the daily measure for the three conditions. We focused on each sub-dimension of response expectancy: Expected Magnitude for Negative Emotions and Expected Strength for Negative Emotions.

Expected Magnitude for Negative Emotions

In the case of negative emotions as the outcome, no significant interaction effect between group * time * optimism for Expected Magnitude for Negative Emotions was found where F (12; 777) = 1.69 and p =.063.

Expected Strength for Negative Emotions

In the case of negative emotions as the outcome, a significant *interaction effect* between group * time * optimism for Expected Strength for Negative Emotions was found, F (12; 776) = 1.94, $p < .026$. Therefore, we examined how the conditions, time, and optimism levels interact to influence the Expected Strength for Negative Emotions levels.

In the case of low optimism, pairwise comparisons for the first day (when the intervention is absent) indicated a significant difference between the Negative and Control Conditions ($t = 2.69$, $p < .022$). Pairwise comparisons during the intervention (when information and intervention are present) indicated a significant positive difference between the Negative and Control Conditions in the case of Day 3 ($t = 2.70$, $p < .015$), Day 4 ($t = 2.43$, $p < .023$), Day 6 ($t = 3.31$, $p < .001$) and Day 7 ($t = 3.33$, $p < .002$), respectively a significant positive difference between the Positive and Control Condition in the case of Day 3 ($t = 2.58$, $p < .015$), Day 4 ($t = 2.58$, $p < .023$), Day 5 ($t = 2.67$, $p < .023$), Day 6 ($t = 4.55$, $p <.001$), and Day 7 ($t = 2.91$, $p < .005$),

In the case of medium optimism, pairwise comparisons for the first day (when the intervention is absent) indicated a significant positive difference between the Negative and Control Condition ($t = 3.57$, $p < .001$), respectively, a significant negative difference between the Positive and Negative Condition ($t =-2.40$, $p < .025$). Pairwise comparisons during the intervention (when information and intervention are present) indicated a significant positive difference between the Negative and Control Condition in the case of Day 3 ($t = 2.52$, $p < .036$), Day 6 ($t = 2.94$, $p < .010$), and Day 7 ($t = 2.60$ $p < .029$), respectively a significant positive difference between the Positive and Control Condition in the case of Day 6 ($t = 2.20$, $p < .042$).

In the case of high optimism, pairwise comparisons for the first day (when the intervention is absent) indicated a marginally insignificant effect between the Negative and Control Condition ($t = 2.10$, $p = .058$), respectively between the Positive and Negative Condition ($t = -2.07$, $p = .058$). Pairwise comparisons during the intervention indicated any significant difference between the conditions.

5. Discussion

Contrary to our hypothesis, the data revealed that the groups did not significantly differ in positive and negative emotions reported at post-intervention or follow-up. The absence of a significant effect on results could be attributed to one of three possible explanations. One possible explanation could be that the provided instructions were not sufficiently solid, credible, and compelling to elicit an effect. Another possible explanation for the lack of significant differences in outcomes between the groups could be that response expectancy regarding positive affect is a relevant mechanism with a major impact on outcomes in a laboratory context but not necessarily in ecological contexts, as illustrated by previous studies (e.g., Geraghty, 2010; Hyland & Whalley, 2008). In ecological contexts, individual differences, such as self-selection, motivation, effort, and person-activity fit, may play a more critical role in the effectiveness of self-help online interventions (Waits, 2017). The last possible explanation for the obtained findings could be that response expectancy is not the primary mechanism through which the gratitude intervention works. More research is needed before solid conclusions can be drawn.

Moderation effects

In the current study, our objective was to replicate the optimism moderating effect, as demonstrated by Geers and Lassiter (2002), on both positive and negative emotions. However, we introduced an intermediate target variable (medium optimism) to gain a more nuanced understanding. The moderation analyses yielded significant results, suggesting that various levels of optimism interact differently with positive and negative expectancies in influencing emotional outcomes, particularly positive emotions, following a positive intervention. This underscores the importance of tailoring interventions to specific populations to maximize their benefits (Kloos et al., 2022; Waits, 2017).

Low Optimism

Individuals with low optimism in the Positive and Negative Conditions benefited significantly immediately after the intervention. This result emphasizes the potential benefits for pessimistic individuals when provided with clear and explicit positive response expectancies regarding the intervention. However, it is crucial to interpret our findings with caution, especially in the case of low optimism in the Negative Condition, as we had only one participant in this category, preventing us from making firm conclusions. However, our result aligns with another study, demonstrating that pessimistic individuals with positive or negative expectations for the same funny film clip reported increased positive affect (Geers & Lassiter, 2002). Our findings are consistent with previous meta-analyses (Davis et al., 2016; Dickens, 2017; Wood et al., 2010), suggesting that short gratitude interventions can benefit pessimistic individuals, especially in the short term.

Medium Optimism

Individuals with moderate optimism across all intervention conditions experienced significant and consistent benefits from the gratitude intervention. They reported increased positive emotions immediately after the intervention, and importantly, this positive effect was maintained a month later, irrespective of the type of expectancy instructions (positive, negative, or ambiguous) they received regarding the intervention's effectiveness.

High Optimism

Individuals with high optimism in both the Positive and Control Conditions experienced significant immediate benefits after completing the intervention, and these benefits persisted at follow-up. Specifically, optimistic individuals who received positive or ambiguous (absent) expectancies reported significantly higher positive emotions post-intervention and a month later than optimistic individuals in the Negative Conditions.

In the case of optimistic individuals in the Negative Condition, our data indicated a non-significant increase in positive emotions at the end of the intervention and follow-up. A similar pattern was observed in a study by Geers and Lassiter (2002), where optimists exposed to negative expectations for a positive experience reported lower levels of positive affective reactions and less enjoyment of the experience compared to pessimists in the same condition. Interestingly, the same authors suggested that when no expectations were given, optimistic individuals reported more positive affect after an enjoyable film clip than pessimists in the same condition, similar to our results. Given these findings, the influence of response expectancies on emotional outcomes appears evident in the case of optimistic individuals.

Daily measures

The dynamic interaction between optimism levels and response expectancy dimensions during the intervention phase holds clinical significance. Constant measurement of response expectancies allows us to capture their fluid nature in response to new experiences, including interactions with the technique (Kirsch, 2018).

On Day 1, when information about the intervention's efficacy was presented without prior experience with the technique, pessimistic individuals and individuals with a medium optimism level from the Negative Condition reported a higher subjective probability (strength of the expectancy) of experiencing negative emotions compared to their counterparts in the Control Condition. Optimistic individuals from the Positive Condition indicated a lower subjective probability (strength of the expectancy) of experiencing negative emotions than optimistic individuals from the Negative or Control Condition. Similarly, individuals with medium optimism from the Positive Condition reported a lower subjective probability (strength of the expectancy) of experiencing negative emotions than their counterparts in the Negative Condition. Following this logic, psychotherapists must be sensitive to individuals' optimism levels in the clinical field before providing an appropriate dosage of positive expectancy to optimize results.

During the intermediate days, when instructions and the experience with the technique co-occurred, individuals with low and medium optimism levels from the Negative Condition maintained a higher subjective probability (strength of the expectancy) of experiencing negative emotions compared to individuals in the Control Condition. This result partially confirms our hypothesis and suggests that continuous negative expectations had an impact even when the participants had systematic experience with the positive technique, particularly for individuals with low or medium levels of optimism.

Limitations and Future Directions

Findings from this study need to be interpreted in light of several limitations. First, the study recruited a convenience sample through social media and university groups. Most participants were healthy individuals from a collectivistic culture with higher levels of well-being, which may limit the generalizability of the results. Future studies should aim to replicate these findings on a more diverse sample, considering cultural and sociodemographic backgrounds and clinical status. Notably, individuals with low or high optimism were underrepresented in our sample, especially at the follow-up measure (e.g., Negative Condition). Second, our sample predominantly consisted of women. Therefore, it is important to replicate these results with gender-balanced samples. Third, the study had a high dropout rate, typical of self-guided online interventions. Our findings may not be generalizable to laboratory-based research when participants are more motivated by extrinsic factors.

Conclusions

Our results add to the body of knowledge, indicating that a brief daily practice of listing things to be grateful for can serve as an efficient, low-cost, and ecological way to decrease negative emotions and enhance positive emotions in healthy individuals. While response expectancy was not found to be the primary mechanism in the effectiveness of gratitude interventions, our findings indicate that some response expectations (e.g., response expectancy for positive emotions) may be more effective than others in achieving the desired outcomes. Furthermore, our findings showed that the intervention effect above positive emotions was moderated by the level of optimism at the beginning of the intervention. In the Positive Condition, individuals with high or medium optimism benefited post-intervention and follow-up, while pessimistic individuals benefited only post-intervention. In the Negative Condition, those with medium optimism benefited considerably post-intervention and follow-up. In contrast, for only pessimistic individuals from this condition, the benefit seems to be short-term (post-intervention). For the Control Condition, only individuals with high or medium optimism benefited significantly from the intervention, while pessimistic individuals did not. Overall, our results suggest that the expectation of positive outcomes (e.g., response expectancy for positive emotions) can enhance the beneficial effects of a gratitude intervention in some instances. These findings can assist researchers and practitioners in creating, customizing, implementing, and developing future gratitude-based interventions.

CHAPTER IV. GENERAL CONCLUSIONS AND IMPLICATIONS

On the conceptual level, we focused on exploring the multifaceted association between response expectancy and positive emotions. Specifically, we aimed to determine whether response expectancy and positive emotions are significantly associated and how this relationship evolves over time. Additionally, we investigated the potential mediating role of response expectancy in influencing positive emotional outcomes. Each of these objectives was systematically analysed across the first three studies. The findings from these studies provide a nuanced understanding of the interconnection between response expectancy and positive emotions, the trajectory of this relationship, and any patterns or changes that occur over time and across different contexts. In the last two studies, we aimed to investigate the role of varying response expectancies (positive, negative, or no expectancies) in impacting positive emotions following two positive interventions delivered both in a laboratory context and a real-life scenario. These findings offer significant contributions on both theoretical and practical levels, addressing a critical gap in understanding how response expectancy impacts positive emotions in positive contexts.

4.1. THEORETICAL, CONCEPTUAL AND CLINICAL IMPLICATIONS

The first objective of the present thesis was to quantify the relationship between emotional prediction and positive emotions. To achieve this, we conducted two separate meta-analyses. The first analysis examined the strength of the association between emotional predictions and experienced emotions (Study 1a). The second analysis investigated the magnitude of the discrepancies between these predictions and actual experiences (Study 1b). Our findings demonstrated that predictions are generally accurate in a relative sense, supported by response expectancy theory (Kirsch, 1985, 1990), with a medium to large effect size for this association ($r = 0.45$). However, when considering the absolute inaccuracy of these predictions, our results reveal a small but statistically significant effect size for the discrepancies ($g = 0.18$), consistent with the affective forecasting framework (Gilbert & Wilson, 2007, 2009). Based on the theoretical model introduced by Coteț and David (2016), which considers affective forecasting a sub-component of the response expectancy dimension, we proposed to explore the nature of the association between response expectancies and positive emotional experiences. To our knowledge, we conducted the first metanalytic study in which specific theoretical and demographic moderators were tested for the relation between emotional predictions and positive emotions as outcomes. On a conceptual level, our findings not only quantified the relationship between emotional predictions and positive emotions, extending the number of studies on positive outcomes included in the previous meta-analysis by Cotet and David (2016) but also demonstrated that specific moderators played a significant role. The nature of the event, the frame of reference for experience, and the percentage of female participants influenced both relationships. Specifically, the accuracy of emotional predictions was higher when anticipating positive emotions associated with positive events (Study 1a). Conversely, inaccuracies were more pronounced when predicting positive emotions in the context of negative events (Study 1b). Additionally, the association between predictions and positive emotions was stronger when emotions were reported regarding a specific focal event (Study 1a). In contrast, the discrepancies between predictions and actual emotions were more evident when emotions were reported in general terms (Study 1b). Finally, the proportion of female participants significantly impacted emotional accuracy in both relative and absolute terms.

The second objective was to explore the mediating role of response expectancy between generalized expectancies and positive emotions, measured both subjectively (positive emotions and relaxation states) and physiologically (SCL, RMSSD, and HR). Specifically, Study 2 conducted eight parallel mediation analyses to examine the influence of response expectancy (in terms of both magnitude and strength) on the relationship between optimism and various non-volitional outcomes (relaxation states, positive emotion, HR, RMSSD, and SCL). The results from the first four models indicated that only the magnitude dimension of response expectancy for relaxation significantly mediated the relationship between optimism and relaxation states, and between optimism and skin conductance levels (SCL), a physiological marker of emotional arousal. These results suggest that optimism about the future does not automatically lead to positive outcomes, such as relaxation in a specific context. Instead, a high response expectancy regarding the magnitude of relaxation is essential for experiencing relaxation in particular situations. Concerning the last four tested models, our findings revealed that neither dimension of response expectancy (magnitude nor strength) for positive emotions mediated the relationship between optimism and positive emotions, either at the subjective or physiological levels (HR, RMSSD, and SCL). On a theoretical level, this study addressed a gap in the literature by testing the concurrent contribution of the magnitude and strength dimensions of response expectancy, clarifying their distinct role concerning non-volitional outcomes. At a practical level, the current findings indicate that positive instructions emphasizing the magnitude of a relaxation intervention's impact might be crucial for enhancing its effectiveness. Specifically, fostering response expectancy for specific emotions, such as relaxation, might be more beneficial than inducing response expectancy for general positive outcomes, like positive emotions, in promoting better treatment adherence.

The **third objective** of our research was to longitudinally investigate the relationships between different positive expectations (response expectancy, response hope, and optimism) and positive emotions experienced in the short term (T0 - T1, two weeks) and long term (T0 - T2, four months) during the COVID-19 pandemic. The first goal of this study was to determine which type of expectancy best predicts positive emotions in the short term and long term. As anticipated, our findings indicated that response expectancy predicted positive emotions in the short-term (two weeks later - T1), optimism predicted positive emotions in the long-term (four months later - T2), and the discrepancy score (Response Hope - Response Expectancy) negatively predicted positive emotions in the short term (T1). The second goal of the longitudinal study was to explore the bidirectional dynamic relationships between positive emotions and positive expectancies. Our results supported a short-term reciprocal interaction between expectancies and positive emotions. Long-term, however, only optimism affects positive emotions. Regarding the response expectancy contribution, our findings demonstrated its beneficial effect in determining positive emotions and positive cognitions (e.g., response hope) in the short term while facilitating a positive mindset (optimism) in the long term during an adverse context, such as the COVID-19 pandemic. From a theoretical perspective, the current findings enhance our understanding of the robust interaction between positive expectancies and the maintenance of positive emotions during stressful periods. This is the first study to integrate all these variables in a longitudinal design, thereby increasing our understanding of the protective factors involved in a resilient response during crises. Finally, on a practical note, these results underscore the importance of clinical practitioners vigilantly monitoring patients' expectancies during crises. Enhancing response expectancy for positive outcomes is crucial for improving individuals' psychological well-being, and addressing unrealistic or unhelpful beliefs can significantly impact their progress. Reducing the discrepancy score (increasing the response expectancy level for positive outcomes) may also be relevant for increasing optimism and positive emotions and reducing distress under challenging situations.

The **fourth objective** of our study was to manipulate response expectancies and assess their influence on emotional experiences through two separate studies. Specifically, we explored whether providing positive, negative, or no expectancies regarding the efficacy of a positive intervention would lead to differences in emotional outcomes.

In Study 4, we conducted an experimental investigation to explore the impact of response expectancies on emotional outcomes (positive emotions in general and relaxation) and physiological levels (HR, RMSSD, and SCL), employing a technique known as "Safe Place" imagery. This intervention took place in a single session within a controlled laboratory setting and was designed to observe the immediate effects of manipulated expectancies on participants' emotional states in a controlled environment. Our hypothesis concerning the emotional outcomes (relaxation states and positive emotions) was partially supported. Specifically, after controlling for baseline levels of positive emotional outcomes, individuals in the Positive Condition reported significantly higher levels of relaxation and positive emotions after the induction than those in the Negative Condition. However, no significant differences existed between the Positive and Control Conditions or between the Negative and Control Conditions. This suggests that explicit and well-defined expectancies, whether positive or negative, can significantly influence emotional experiences following a positive mood induction procedure. From a clinical perspective, maintaining positive expectancies about the effects of a psychological technique (e.g., Safe Place Imagery) can enhance its effectiveness and produce beneficial outcomes, such as increased levels of positive emotions and relaxation. Conversely, negative expectancies may reduce its efficacy and lessen these positive effects. Our findings regarding physiological outcomes (HR, RMSSD, and SCL) offer important insights into the varying effects of positive, negative, and neutral expectancies. Specifically, after controlling for baseline levels, individuals in the Positive Condition exhibited higher SCL levels than those in the Control Condition. This result suggests that positive expectancies can significantly influence physiological arousal levels. Such findings are particularly relevant for interventions promoting relaxation, demonstrating that positive expectancies towards a relaxation technique (e.g., expecting relaxation and comfort from an imagery exercise) can effectively modify physiological arousal. At a practical level, these results emphasize the importance of practitioners actively monitoring and managing expectancies to enhance therapeutic effectiveness. By boosting response expectancy for positive outcomes and modifying negative ones, clinicians can improve emotional and physiological responses to treatment.

In Study 5, we expanded our research into a more naturalistic setting by conducting a randomized controlled trial (RCT) to assess the influence of different response expectancies on emotions within a positive intervention framework. This intervention was carried out over seven consecutive days in an ecological context, allowing us to evaluate the prolonged impact of expectancy manipulations on emotional outcomes over time and in participants' daily environments. Additionally, we sought to investigate whether optimism levels influence the relationship between specific types of expectancies (positive, negative, and ambiguous) and emotional outcomes (both positive and negative). We also examined how the strength and magnitude of response expectancy influence these emotional outcomes. Regarding the primary analysis, contrary to our hypothesis, the data revealed no significant differences in positive and negative emotions reported post-intervention or at follow-up among the groups. However, our findings indicate that response expectancy, as a mechanism involved in the efficacy of psychological interventions, is a complex phenomenon. On a conceptual level, our secondary analysis suggested that emotional outcomes (e.g., positive emotions) are not exclusively influenced by congruent response expectancy valence (e.g., response expectancy for positive emotions) but also by expectations with the opposite valence (e.g., response expectancy for negative emotions). Ultimately, our results support the interaction between specific expectations and a person's level of optimism (low, medium, and high) in shaping emotional responses. Notably, individuals with low optimism in the Positive and Negative Conditions benefited significantly immediately after the intervention. Individuals with moderate optimism across all intervention conditions experienced reported increased positive emotions immediately after the intervention and follow-up. Individuals with high optimism in both the Positive and Control Conditions experienced significant immediate benefits after completing the intervention, and these benefits persisted at follow-up. On a practical note, these results underscore the importance of customizing interventions to cater to specific populations to maximize their effectiveness.

4.2. Methodological Advances

In addition to the theoretical and clinical implications discussed earlier, this thesis addresses several methodological gaps in the literature on response expectancy for positive emotions. Firstly, by employing a meta-analytical approach, we gained a more precise insight into the associations between expectancies and positive emotions. Secondly, using a longitudinal design, we significantly advanced in understanding the influence of response expectancies on positive emotional outcomes over time—a previously unexplored relationship. This method highlights temporal changes, filling a crucial gap in the existing literature. Additionally, experimental designs represent a significant improvement over the predominantly correlational nature of prior studies, offering substantial contributions to the field.

One essential contribution of this research is the confirmation that response expectancy can influence non-volitional outcomes at both subjective and physiological levels—a finding aligned with several previous studies (e.g., Rutherford et al., 2016; Wang et al., 2020; Kwan et al., 2017; Mothes et al., 2017; Peerdeman et al., 2016; Faria et al., 2017; Kube et al., 2020; Vase & Wartolowska, 2019). Specifically, we demonstrated that response expectancy is related to positive emotions in both dimensions (subjective and physiological) during positive mood induction procedures in laboratory settings, utilizing VR relaxation applications (e.g., Nature Treks VR - Green Meadows) and imagery techniques (e.g., Safe Place). Moreover, our research tested the efficacy of various positive interventions and explored their mechanisms of change, providing important insights into how these interventions may work. Additionally, using randomization procedures and active control groups enhances the validity of our findings. All positive interventions employed in our studies had high ecological validity. In Study 2, the VR application simulated a nature walk. The experiential technique in Study 4 involved imagining a safe place, and in Study 5, the gratitude diary was administered online via mobile phone. Study 3's context was the complex and real-world scenario of the beginning of COVID-19 pandemic.

Finally, another methodological contribution of our research is the concurrent investigation of response expectancy dimensions—magnitude and strength—across multiple studies (Study 2, Study 4, and Study 5), a combination rarely examined within the same research framework. Furthermore, we assessed response expectancy in relation to general positive emotions (Study 3 and Study 5) and specific positive emotions like relaxation (Study 2 and Study 3). In Study 5, we measured response expectancy multiple times to better capture its dynamic nature.

4.3. General Conclusions

The primary results derived from the studies included in this thesis can be summarized as follows:

1. Through the meta-analytic study, this work contributes to the literature on emotional predictions and positive emotions. Study 1a demonstrated a medium to large effect size for this association (r = 0.45), while Study 1b showed a small but statistically significant effect size for the discrepancies (g = 0.18). The valence of the event, the frame of reference for experience, and the percentage of female participants moderated both relationships.
2. The magnitude dimension of response expectancy for relaxation significantly mediated the relationship between optimism and relaxation states and between optimism and skin conductance levels (SCL), a physiological marker of emotional arousal.
3. Response expectancy predicted positive emotions in the short term, optimism predicted positive emotions in the long term, and the discrepancy score (Response Hope—Response Expectancy) negatively predicted positive emotions in the short term. Also, in the short term, expectancies and positive emotions were reciprocally associated, while in the long term, only optimism predicted positive emotions.
4. Response expectancies can influence subjective and physiological levels. Individuals who received positive expectancies reported significantly higher levels of relaxation and positive emotions (after controlling for baseline levels) after the positive induction than those who received negative expectancies. Also, after controlling for baseline levels, individuals who received positive expectancies reported significantly higher skin conductance (SCL) (after controlling for baseline levels) after the positive induction than those who received no explicit expectancies.
5. A short daily gratitude intervention proved to be an effective, low-cost, and ecological method for reducing negative and increasing positive affect, regardless of individuals' expectancies (positive, negative, or none). Response expectancies were not a significant mechanism driving the efficacy of the gratitude intervention delivered in an ecological context. However, secondary analysis indicated that varying levels of optimism (low, medium, and high) interact differently with positive and negative expectancies in influencing emotional outcomes, particularly positive emotions.

4.4. Limitations and Future Directions

One significant limitation of this thesis is the sample's representativeness, as participants were recruited through social media and university groups. The samples in our studies predominantly consisted of females, relatively young, primarily undergraduate students, who were entirely Caucasian and from a collectivistic society. This lack of diversity in our sample restricts the generalizability of our findings. It is crucial for future research to replicate these findings using larger and more diverse samples. This includes older community members, achieving a more balanced gender distribution, and incorporating participants from various ethnic groups. The inclusion of diverse samples will enhance the applicability of our findings to a broader population.

Another important avenue for future research involves replicating our results in clinical populations. For instance, individuals with clinical anxiety, who often have difficulties with relaxation, may exhibit specific types of response expectancies, such as those for relaxation (e.g., response expectancy for relaxation). Conversely, individuals with depression are characterized by pessimistic expectancies about life, others, and themselves, which can interfere with their response expectancies for positive emotions. Therefore, the complex interaction between cognitions and emotions in clinical samples necessitates further investigation into how response expectancies for positive emotions affect the corresponding emotional experiences.

While Studies 1, 2, 3, and 4 demonstrated the association between response expectancies and positive emotions, this relationship was not observed in Study 5. To reconcile this inconsistency, future research should provide sufficiently robust, credible, and compelling instructions. Employing multiple modes of information delivery, such as verbal, written, and video formats, might enhance effectiveness. Developing a comprehensive and credible rationale that boosts confidence in the expected outcome is crucial, especially in ecological settings such as adherence to online interventions.

Finally, some notable methodological limitations in our studies are worth mentioning. While we evaluated response expectancies related to specific and general positive emotional outcomes, we used a single item to measure general positive emotions in Studies 4 and 5. Conversely, in Study 3, a single item measured response expectancy specifically for relaxation. Although single-item measures are known for their reliability in assessing unidimensional constructs, future research should employ more comprehensive measures that include a broader range of items to evaluate this construct better. Pursuing this line of research would be highly beneficial for future studies to explore whether the impact of response expectancies on positive emotions varies depending on arousal levels. Specifically, it is crucial to investigate the accuracy of response expectancies in influencing emotions characterized by low arousal levels, such as relaxation, and moderate arousal levels, such as joy, versus those with high arousal levels, such as excitement. Conducting comparative studies on positive emotions with varying arousal levels is essential to enhance our understanding of the role of response expectancy in shaping positive emotionality.

While Studies 2 and 3 demonstrated the contribution of response expectancies (e.g., response expectancies for positive emotions) in impacting physiological markers associated with positive emotional experiences, such as Skin Conductance Level (SCL), but no others, such as Heart Rate (HR) and Root Mean Square of Successive Differences (RMSSD), future studies are needed. For example, more rigorous objective measures such as functional Magnetic Resonance Imaging (fMRI) methods could provide more conclusive and valuable insights into the biological mechanisms underlying expectancies and positive emotional outcomes. The use of fMRI methods in future studies holds great potential in providing more conclusive and valuable insights into the biological mechanisms underlying expectancies and on the experience of positive emotional outcomes.

Considering the dynamic nature of expectancies, future studies are necessary to capture the evolution of response expectancies and their impact on non-volitional outcomes. Even in Study 5, where we measured response expectancy several times during the intervention phase, the interaction between expectancies and positive emotions as outcomes still needs to be addressed. Employing ecological momentary assessments (EMA) would capture real-time data on emotional responses in naturalistic settings. This approach would enhance our understanding of the dynamics between response expectancies for positive emotions and emotional experiences in daily life. However, discrepancies and congruencies can be addressed by comparing laboratory-based findings with EMA data, offering a more nuanced understanding of how response expectancies shape emotional experiences outside controlled environments. Additionally, future research could employ more advanced statistical methods, such as network analysis, to better capture the role of response expectancy in relation to emotional functioning.

Another valuable research avenue involves examining dispositional traits as moderators in the relationship between response expectancy and positive emotional outcomes. It is crucial to determine whether the impact of response expectancy on emotions varies based on differences in dispositional traits. For example, future studies could explore how variations in an individual’s mindfulness disposition influence the alignment between response expectancies and actual emotional outcomes.

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