# Happiness at Work: the impact of Affect Experience on Organizational Outcomes.

## An Experience Sampling perspective

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# Declaration

I, Ana Rita Camilo Lopes, confirm that the work presented in my thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

## Abstract

Studies regarding happiness at work appear to rely mostly on cross-section and aggregate data that require accurate memory encoding and retrieval and dismisses the relevance of time as a variable in the Subjective Well-Being (SWB) equation. The experience sampling (ESM) methodology enables researchers to collect disaggregated, real time, multilevel data that permits the inclusion of time varying effects, such as work activities and social interactions in the workplace and examine their relationship to happiness. This thesis contributes to the understanding of how happiness fluctuates over time by considering the state-like affective component of SWB through the development of a happiness experience sampling mobile app. Happiness was evaluated as an outcome of individual differences (temporally stable) and situational aspects (time varying), before it was placed in the role of an antecedent of productivity in the workplace.

The studies in this thesis are longitudinal and rely on ESM. International participants provided repeated momentary happiness ratings (N=192 and N=111 were used for the studies) which demonstrated that (a) temporally stable predictors (such as personality) of happiness were weaker than the literature suggested, (b) situational parameters were stronger predictors of momentary happiness fluctuations and explained a larger proportion of its variance, and (c) time varying happiness and situational factors significantly predicted self-assessed productivity perceptions.

Theoretical and methodological discussion points are raised, including the need for a better consideration of the relevance of time as a variable in the study of SWB, and the need to continue to research the affective component of SWB to a higher extent, and through the use of longitudinal, experience based, methodologies. The development of a reliable and reusable happiness experience sampling mobile app also has the potential to improve employers' capabilities to make decisions, as well as boost interest in their workforce's happiness and contribute to practice.

**Impact statement**

With the increasing interest in the topic of subjective well-being in various walks of life, be it from a perspective of workplace conditions, mental health, social context, or policy changes, it is critical to understand what impacts the way in which the affective component of subjective well-being fluctuates, is affected, and impacts other variables. The work in this thesis focused on occupational psychology scholarship, and the way in which affect is experienced, its antecedents, and its outcomes is of critical relevance. The research presented in this thesis may be grouped into two main domains:

- Novelty methods: developing a new method for measuring in the moment affect experiences.
- SWB in the workplace: deepen understanding of SWB in real time situations without experimental manipulation.

Given the nature of this project and the aim to improve the theoretical and empirical knowledge surrounding the measures and methods used in the field of subjective well-being, the benefits of this research will be suitable for three principal groups, with no geographical restrictions.

Firstly, this research will benefit academics interested in the field of subjective well-being or methods pertaining to the use of disaggregated real time, longitudinal, multilevel data to understand naturalistic experiences of individuals. The impact will be felt primarily through the dissemination of the findings via contribution scholarship, presentations, and teaching within higher education.

Secondly, the work presented in this thesis will benefit practitioners. As the key demographic of professionals within organisations who specialise in individual and organisational subjective well-being, the knowledge generated by this research has far-reaching potential impact and may be used to improve or develop internal policies, interventions, or learning and development initiatives. These professionals may include occupational psychologists, human resources, or other workplace specialists, as well as data scientists.

Finally, this thesis' outcomes will benefit those who make decisions that are likely to impact others significantly, or themselves as individuals: employers (within the public or private sector), certain professionals, or organisations (e.g., managers of any level; organisational well-being leads; learning and development decision makers; organisations who focus on well-being or mental health at the workplace, etc.).

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*I dedicate this work to my grandmother, who never wished for anything other than for me to "keep studying and be happy" and was one of the most incredible women I have met and was lucky to grow up with.*

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## Chapter 1: Introduction

The notion of being happy as one of life's ultimate goals is not new. Since the beginning of time, humanity has looked for the meaning of life, often tying it with an ever-elusive concept of achieving undeniable happiness. From times of early civilisations, how to achieve well-being was a question that occupied intellectual, religious, or philosophical minds (Diener, Oishy, et al. 2018). In recent times, outside of academia, measures and indicators of subjective well-being have been used and referred to as a reliable source of context when it comes to understanding people's quality of life and overall circumstances, at the population level. Some well-established and reliable examples include the Organisation for Economic Co-operation and Development (OECD), the World Health Organisation (WHO), or the development and yearly publication of the World Happiness Report (e.g., the 2024 report by Helliwell et al., 2024). A closer examination of these outputs not only highlights key insights that contribute to the understanding of subjective well-being through various lenses, they also emphasise how the use of the terminology differs between them, based on how the construct is operationalised, and how the contributions are advanced. While the OECD well-being framework includes, for example, a conceptual distinction between current and future well-being, where the former includes subjective well-being as a component of current well-being, amongst a set of ten other constructs (e.g., income and wealth, housing, health, knowledge, and skills, etc.) (Stiglitz et al., 2018), the report by Helliwell et al. (2024) follows a subjective well-being operationalisation as defined by Diener et al. (2017), which includes measuring a cognitive element of life satisfaction, and an affective experience component that reflects both positive and negative affect. The upcoming section will continue to examine and consider the different definitions of subjective well-being and happiness from a scholarship and research point of view, before progressing to discuss the thesis' research conceptual model, scope and outline.

### *1.1 Defining SWB and happiness: science and society*

The use and understanding of happiness-related constructs, methodologies and measures is the cornerstone to the advancement of the of the well-being field. A clear definition and understanding are critical for accurate decision-making with regards to organisations, policy improvements, and population well-being in general. A multitude of definitions and terms have been used over the past decades that seek to define and encapsulate what is often broadly labelled as happiness and/or well-being. It has proven difficult to establish exactly what happiness is and how to measure it (Stewart, et al., 2010; Hills & Argyle, 2001). The interchangeable use of concepts such as “happiness”, “life satisfaction”, “health”, and “subjective well-being” occurs with some frequency (Swami, 2008; Diener 2000), complicating the matter further. In science writing and peer reviewed manuscripts, the terms “happiness” and “subjective well-being” have primarily been used interchangeably. In some instances, it may have been the case that based on the scholarly writing the reader is informed that “subjective well-being” includes and encompasses “happiness”, and in other instances that “happiness” includes and encompasses “subjective well-being”. For the most part and more frequently, however, they have been used as synonyms, with the term “happiness” being used in context-appropriate situations (e.g., to refer to how laypeople may think of these constructs), and the term “subjective well-being” as its scientific counterpart which has been provided with a theoretical framework, and thus allows for a measurable definition that can be shared and replicated by authors. The fact that the word happiness itself is commonly used, by scientists and laypeople alike, in every-day conversations confounds the topic further. Interestingly, in its every-day use, it is not necessarily any easier to define than the challenges that it poses for scientists and researchers. It can be seen as a passing feeling (in line with “joy”, for example), a feeling of achievement, or a long-term process regarding one’s pursuit of relevant goals and ideals (Delle Fave et al., 2011).

To further highlight the many variations of the definitions used to refer to "happiness" or "subjective well-being" in the context of scientific knowledge, a summary is offered in table one. The definitions are chronologically presented to enable an intuitive historical perspective of its evolution since the 1980s. While the table is not an exhaustive list of all definitions present in the literature, it is a useful summary that denotes the similarities and discrepancies seen over time. For older definitions, Coan (1977) has written a review of earlier conceptualisations, definitions, and terminology which might be useful. The table below includes examples extracted from publications since the mid-eighties and includes a minimum of one definition for each decade.

**Table 1**

*Definitions and conceptualisation of "happiness" and SWB.*

| Terminology used | Definition provided | Source |
| --- | --- | --- |
| Life satisfaction as a component of subjective well-being | "*Life satisfaction refers to a cognitive, judgmental process. (…) Judgments of satisfaction are dependent upon a comparison of one's circumstances with what is thought to be an appropriate standard. (…) judgment of how satisfied people are with their present state of affairs is based on a comparison with a standard which each individual sets for him or herself; it is not externally imposed.*" | Diener, Emmons, Larsen and Griffin (1985), p. 71 |
| Happiness as hedonic happiness | *"(a) an unusually intense involvement in an undertaking, (b) a feeling of a special fit or meshing with an activity that is not characteristic of most daily tasks, (c) a feeling of intensely being alive, (d) a feeling of being complete or fulfilled while engaged in an activity, (e) an impression that this is what the person was meant to do, and (f) a feeling that this is who one really is*" | Waterman (1993), p. 679 |
| Happiness and subjective well-being as a synonym | "*SWB consists of three components: life satisfaction, the presence of positive mood, and the absence of negative mood, together often summarized as happiness.*" | Ryan and Deci (2001), p. 144 |

| Terminology used | Definition provided | Source |
|---|---|---|
| Happiness and subjective well-being as a synonym | "*Here we define happiness as it is most often defined in the literature, that is, in terms of frequent positive affect, high life satisfaction, and infrequent negative affect. These three constructs are the three primary components of subjective well-being (…)*" | Lyubomirsky, Sheldon and Schdkade (2005), p. 115 |
| Happiness as a result of experiences | "Experiences of pleasure and purpose over time" | Dolan (2014) |
| Subjective well-being as a multifaceted component which includes reactions to what happens around us | "*SWB is defined as people's overall evaluations of their lives and their emotional experiences. SWB thus includes broad appraisals, such as life satisfaction and health satisfaction judgments, and specific feelings that reflect how people are reacting to the events and circumstances in their lives.*" | Diener, Heintzelman, Kushlev, Wirtz, Lutes and Oishi (2017), p. 87 |

Note: These definitions were extracted from publications where the authors referred to "happiness" as a construct.

As highlighted above, it becomes apparent that the use of the words "happiness" and "subjective well-being" has been combined more often than not and it can be seen to frequently be applied interchangeably in scientific writing.

### ***1. 2 Subjective well-being and happiness frameworks in scholarship***

Accurately measuring well-being depends on having a clear definition of what it is that research aims to capture (Dodge, Daly, Huyton & Sanders, 2012). Amongst the definitions presented in the literature, Schueller and Seligman (2010) described subjective well-being as including multiple components such as happiness, life satisfaction, positive affect, negative affect, and depression. What is uncommon about their view compared to other authors, is the inclusion of "happiness" as a component of subjective well-being. Most authors consider happiness and SWB to be the same construct, whereby "happiness" is a loose term difficult to accurately define (thus avoided in scientific writing) and subjective well-being is interpreted as an umbrella-term to include the multiple components that define it (Diener et al., 2017).

In recent years, subjective well-being (SWB) seems to have become the leading choice in scientific writing to refer to how people perceive their lives, and the affects associated with their experiences. Diener and colleagues' (2017) definition mentioned above in table one is frequently cited as the de facto construct in papers written in the last few years. They define SWB as a multifaceted construct that reflects an individual's global cognitive evaluation of their life by resorting to an internal schema that will differ between people, as well as their emotional experiences – both positive and negative affect, i.e., the feelings that result from how individuals perceive, tackle, react, adjust or reflect to the life events and circumstances that they encounter.

In short, as a multi-dimensional construct, SWB may be broken down into its three main components: a cognitive component of life satisfaction, and two affective components: positive and negative affect (Diener, Oishy, et al., 2018; Kahneman & Deaton, 2010; Stewart et al., 2010). The three components have been demonstrated to be distinct, with their variation possible to occur independently (Luhmann et al., 2012; Busseri & Sadava, 2011), leading authors to defend that the components should be measured separately (Carrillo et al., 2021; Sonnentag, 2015; Lucas et al. 1996; Pavot & Diener 2008).

The use of SWB in scientific writing achieves the crucial goal of moving away from earlier tendencies to equate concepts such as satisfaction (or pleasure) to happiness (Delle Fave, Brdar, Freire, Vella-Brodrick & Wissing, 2011). Dolan (2014) proposed that all experiences an individual goes through, meaningful and meaningless, purposeful or not, positive or negative, are relevant and should be seen as experiences rather than cognitive judgements or evaluations. The author proposes that the focus (i.e., attention) that individuals place on their experiences becomes the key to understand why some are happier than others, despite seemingly having gone through "worse" scenarios (the latter of which implies a judgement).

Kahneman (1999) is also a proponent of avoiding taking direct cognitive evaluations as the representation of one's happiness. He says (about participants responding to surveys): 'they do not generally know how happy they are, and they must construct an answer to that question whenever it is raised' (Kahneman, 1999), also surfacing the idea that depending on how the questions are constructed and asked, the answers will be wildly different in terms of what they represent; whether it is satisfaction, joy, meaning, pleasure, or a different construct.

This thesis focuses, exclusively, on the affective component of SWB – positive and negative affect – and does not address the cognitive component – satisfaction. Throughout this manuscript, the terms "happiness", and "well-being" may be used to refer to the affective component of SWB in the context of the present research. When referring to or reporting on existing literature, the terminology will be kept consistent to what the original authors selected as their focal wording.

### *1.3 SWB affective components compared to relevant terminology: transient affective states, mood, and emotion*

As demonstrated in the previous sections dedicated to the conceptual challenges that surround the field of "happiness research" and its enmeshment with subjective well-being, it is important to also consider how constructs that are related to affective experiences are conceptualised, and distinguished, from the affective component of SWB in focus throughout the present work.

Firstly, it could be questioned whether "emotion", "mood", and "affect" might be synonyms, or whether these are independent and separate psychological constructs. A revision of the literature in this field is as muddled as the one on SWB when it comes to distinguishing and separating notions in order to enable adequate investigation (Ekkekakis, 2013). There are multiple examples in the literature where the authors propose different combinations of these terminologies being synonyms (e.g., Boutcher, 1993, where mood is stated to be a synonym of emotion), not synonyms but related (e.g., Terry et al., 1999, where emotion and mood are not classified as synonyms but intrinsically related), or various other theoretical conceptualisations where, for example, emotional states may be considered moods (e.g., Berger & Motl, 2000). This has been the case in the literature despite the fact that from empirical and theoretical standpoint there are signs that are more compatible with an interpretation that separates emotions from moods. Even from a clinical point of view of evaluating, for example, anxiety and mood disorders, these are not classified in the same category, further suggesting that these are separate and distinguishable constructs (Ekkekakis, 2013). This challenge persists even when looking into the measurement of these constructs, rather than simply their theoretical and conceptual definitions, with evidence pointing to the fact that authors may have both mislabelled some scales and what they measure, for example, the Positive and Negative Affect Schedule (PANAS), which states to intend to measure affect (as its name indicates), but simultaneously describes it as measuring mood (Watson, Clark, & Tellegen, 1988) as well as making broad statements about their measures that are not commensurate with the scale descriptions and their items. Examples of the latter could be the conceptualisation of mood as transient affect, and simultaneously that by experiencing affect, then that translates into having a specific mood (Watson & Clark, 1994), and the statement of mood as a synonym to affect (Watson & Vaidya, 2003).

In a 2007 publication, authors Gray and Watson defined “affect is a broader, more inclusive psychological construct that refers to mental states involving evaluative feelings, that is, states in which a person feels good or bad or likes or dislikes what is happening” (p. 171) when compared to emotion and/or mood, which they further considered to be closely related despite important differences between them, such as how intense they may be, how long they may last for, how frequently they may occur and how that translates into activation for the individual.

The relevance of these distinctions is emphasised by the interest of investigating real-time affect which, as the nature of real-time should help make clear, presumes that individuals' affective experiences might change frequently (and potentially quickly) and as such they can result from one's surroundings and not require cognitive involvement (Ekkekakis, 2013) as was proposed earlier by the influential work of Lazarus in the nineties (1991), unlike the notion of emotion which is a response to something as well as directed towards a target.

The literature defines core affect as those feelings that are the most basic level that individuals can intentionally access (i.e., be aware of) that do not have a pre-requisite for them to be aimed at a particular target (Russell & Feldman Barrett, 1999), and can include feeling pleasure or feeling displeasure, feeling a sense of calmness, etc. These are the kinds of affective experiences that individuals feel at all times, regardless of the absence of a specific direction or target. Later, Russell (2003) further explained that "as consciously experienced, core affect is mental but not cognitive or reflective" (p. 148). This specifically clarifies that this lack of cognitive component as well as the fact that it does require the person to engage in reflection is a key defining attribute of the construct. From this perspective, affective experiences would be a part of a system that also includes emotions and moods as separate components, with affect being the broader and more encompassing construct.

Mood and emotion, on the other hand, appear to have traditionally been seen to go hand-in-hand in the literature, with two crucial distinctions: mood is seen as having a longer half-life and lasting for longer periods of time at a lower intensity (even somewhat diffused), whereas emotion is seen to be shorter lived but involves higher activation and therefore partly helping to explain why emotions would not be expected to last as long as a mood state (Nowlis & Nowlis, 1956; Ekman, 1992; Frijda, 2009).

Ekkekakis (2013) proposes that these three constructs can be distinguished based on a few core elements, which can be seen in detail in the author's originally work, however, for a purposeful summary, below is a roundup of some key features that are relevant to understand the upcoming sections of this thesis where the conceptual model and rationale will be detailed. The author suggests that these are elements of distinction between affect, emotion, and mood: a) the rate at which they are present in one's life; b) their intensity; c) their composition; d) whether they are specific to something or e) directed at something; f) whether it has a time-based relation to the stimulus; and g) whether it is affected by cultural aspects. On the topic of whether these constructs are present some of the time versus all of the time (a), the main distinction is that affect is the only of the three which is constantly present, and when combined with its intensity (b), affect is also the only one which could reveal both low or high intensity, depending on the situation, as it directly relates to what happened in the moment (f), not suffering from as much cultural influence as mood or emotion might (g).

Crucially, these clarifications imply that when an affect experience occurs, it may be related to either emotion or mood, but it is not a requirement that this is the case. In other words, an emotion might be considered an affective experience, but an affective experience might not be related to an emotion. According to Eid and Larsen (2007), the fleeting nature of some of our experiences is cause for concern and care within the field of research of subjective well-being, which highlights both the need to implement a research design that can account for these fluctuations (such as experience sampling), as well as measure them longitudinally. While the authors refer to these transient experiences as being "mood" rather than "affect" or "emotion" as discussed above, their perspective speaks to the need to incorporate methodologies and analytical approaches that do not negate the relevance of the real-time experiences in individuals' lives.

Qiao-Tasserit and colleagues (2017) conducted research to investigate the relationship between transient or momentary affective states, mood (sustained), and traits such as anxiety or depression which can be classed as affective traits. Their goal was to determine whether the momentary affective states would produce longer-lasting effects (i.e., mood) within those experiencing them. Their findings showed that negative affect had a larger impact in the sense that they had the potential to affect mood for a period of time, regardless of the stimuli (i.e., affect experience) itself, whereas for positive affect, its ability to influence mood relied more on the engagement produced by the stimuli causing the positive affective experience, and therefore the ability to produce potential bias was higher for the negative affective experiences.

### *1.4 Conceptual research model, context, and rationale*

Having established the distinctions between key concepts, both within the field of SWB at large, as well as related to affective experiences more precisely, this section of the thesis will focus on the conceptual research model that offers context and sets the rationale for the empirical chapters that will be presented. From the distinctions set above, it becomes clearer that:

a) Empirical findings are not always easy to compare due to the complex and vast differences between the definitions and operationalisations proposed by researchers (both for SWB as well as affect, emotion, and mood).
b) Past studies have not dedicated sufficient attention to longitudinal study designs having instead substantially shown an inclination towards cross-sectional designs with an incidence on objective variables and their relation to SWB.
c) The transient nature of individuals lived experiences and how these experiences are perceived and affect us have been neglected and are under-studied. Further, most of the available longitudinal studies have proceeded to analyse data in such a way that the potential longitudinal variation would have been lost (by agglomerating all observations into a mean value).

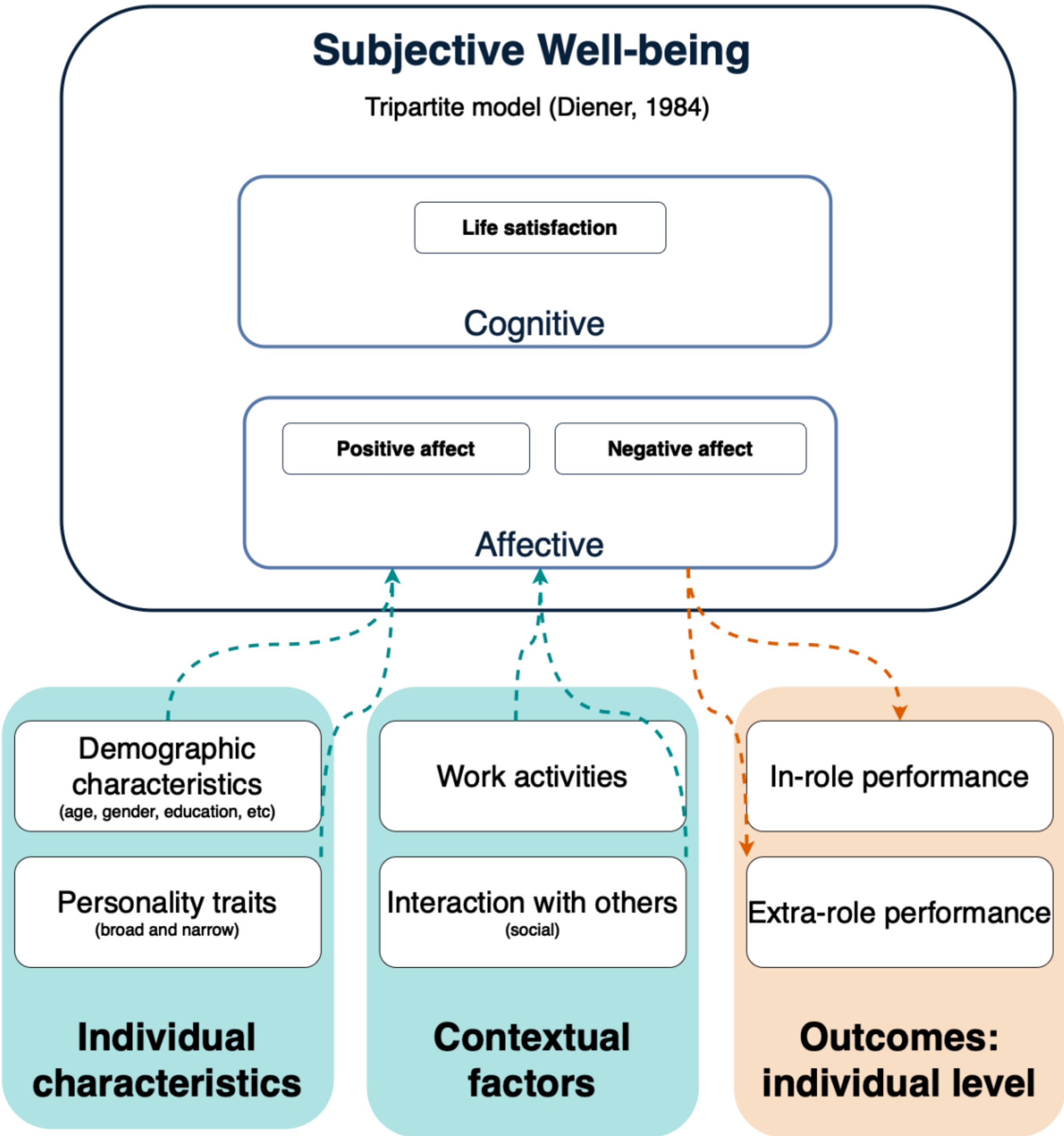
Diener’s (1984) tripartite conceptual framework of SWB is at the core of the work developed in this thesis. As established, this framework positions SWB as a three-factor construct: satisfaction with life, positive affect, and negative affect.

Subsequent research has proposed that contextual factors are an important element affecting SWB, namely by the events experienced by individuals over the course of their lives (Galinha & Pais-Ribeiro, 2011), although these have not been studied widely, and we lack understanding and empirical data form a perspective of realistic and real-time scenarios that may not equate to a “life event” (such as obtaining a new job, or a marriage). This thesis’ conceptual framework therefore aligns closely with the Tripartite SWB framework (Diener, 1984), whilst focusing exclusively on the affective experiences. The three SWB components have been demonstrated to be distinct Luhmann et al., 2012; Busseri & Sadava, 2011) and may vary independently from one another. The combination of these two conditions has led to scientists highlighting the need to measure the components separately to provide a more complete understanding of the framework (Carrillo et al., 2021; Sonnentag, 2015; Lucas et al. 1996; Pavot & Diener 2008).

Considering the lack of longitudinal and real-time data, the thesis conceptual research model is illustrated in figure one will focus primarily on understanding the relevance and interest of measuring real-time experiences as a result of a number of factors (both time varying and time unvarying) as well as whether the affective experiences appear to be related to self-perceptions of performance at work.

**Figure 1**

*Conceptual research model*




The present work will primarily focus on the development of an experience sampling methodology which aimed to collect real-time, naturalistic, continuous data pertaining to individuals' experiences of positive and negative affect throughout their days and investigate two main streams of knowledge: a) the relevance and usability of real-time individual experience data for the study of SWB; b) the use of an experience sampling methodology that collects real-time disaggregated data for analysis. These two streams will guide the reader throughout the thesis and are further clarified below:

a) The primary aim of this stream of research is to develop a novel understanding of how the natural fluctuation of affective experiences affects and relates to time varying occupational antecedents and outcomes of SWB. On the one hand, antecedents of SWB are variables such as individual differences, personality traits, the activities being performed and the social interactions in the workplace happening in the moment; on the other hand, the prime occupational outcome of SWB of interest in this thesis is productivity in the form of in-role and extra-role performance.

b) The main goal of the second stream of knowledge is the development of an experience sampling methodology (ESM) openly available to participants via a smartphone mobile application. Chiefly, it sought confirmation that the recourse to time varying variables in occupational psychology research is a justified alternative methodology that offers many benefits over traditional cross-sectional or longitudinal aggregated data points solutions.

Inspiration for the work presented in this thesis stems from the well-documented need for better conceptual and methodological avenues to continue to understand subjective well-being within the field of positive organisational scholarship. This need is further emphasised by the perceived disconnect between theoretical research and its realistic and naturalistic application within the world of organisations.

Specifically, previous research in the field of subjective well-being has known shortcomings when it comes to the methodologies employed in the past, and these limitations (described below) may have the potential to significantly contribute and shape our understanding of subjective well-being at work.

### *1.5 Thesis outline*

The thesis' chapters are organised around three main knowledge and research anchor points: causes of happiness (i.e., happiness as an outcome);

measurement of happiness at work through an experience sampling methodology; and happiness at work as an antecedent of productivity, an occupational outcome.

Chapter 2 provides a comprehensive literature review of the field of SWB with regards to the causes of happiness. This chapter includes two main perspectives: 2.1) happiness as a result of individual differences (stable or time unvarying factors); 2.2) happiness as a result of context or environment (time varying factors). This chapter constitutes the broad basis for the first and second studies conducted. Chapter 3 revolves around providing a complete overview of the knowledge base behind the measurement of happiness – past, present, and future – and it includes, 3.1) methodological improvements needed within the field and 3.2) the case for experience sampling methodologies and the development of the present study's data collection ESM mobile app. This is a critical chapter to address this thesis second critical aim – to develop a novel experience sampling mobile app with the goal to advance the methodology used in the field of SWB research by demonstrating the value of momentary experience data collection as a rich source of knowledge. Chapter 4 offers an extensive literature review surrounding the topic of workplace happiness and its relationship to performance and productivity. This chapter is the key source that creates the necessary context for the third study in this thesis. Chapter 5 is the full description and analysis of the first study which focuses on using traditional time invariant metrics, such as personal characteristics and individual differences measured via personality inventories, as predictors of time-varying momentary happiness. In this study, happiness is an outcome of time invariant predictors. Chapter 6 depicts the second study which focuses on the contextual and time shifting workplace factors as the predictors of momentary happiness measured with ESM. One of the aims is to demonstrate whether state-like outcomes (such as real-time happiness) are adequately predicted by state-like predictors (such as real-time activities or interactions). In this study, happiness is an outcome of time varying predictors. Chapter 7 includes the third study of this manuscript which investigates the use of time varying variables, including happiness, to predict changes in perceived performance ratings. A goal of this study is to determine whether ESM is a suitable methodology to implement to measure the effect of happiness on occupational outcomes. In this study, happiness is an antecedent of a time varying outcome. The manuscript's knowledge development concludes with chapter 8 which entails an overall discussion of the empirical findings of this thesis' studies, how it contributes to the theoretical and methodological advancement of the field of research of SWB and considers whether the identified gaps were suitably addressed along with remarks regarding the future of this field and directions for future research.

# Chapter 2: Literature Review

## *2.1 Causes of happiness*

Following the definition of happiness as SWB in the initial chapter, the current chapter begins with an overview of the causes of happiness reviewed in previous literature within the field of SWB to further clarify what research has found to contribute to increased or decreased happiness feelings. The antecedents of happiness will be approached from two angles: those that stem from individual differences, and those that are external to the individual (such as context).

## *2.2 Antecedents of happiness*

The remainder of this chapter details the state of the existing literature regarding internal or external antecedents of happiness. For the purpose of this thesis, antecedents of happiness were considered as belonging to one of the two binary categories aforementioned. An antecedent of happiness was considered internal if its primary source is the individual themselves – this includes any personal characteristics and could range from genetic or biological predispositions to demographic characteristics, or personality traits. Given the scope of this thesis, the focus will be on personal demographic characteristics and personality traits (Bartels, 2015; Costa & McCrae, 1980; Weiss, 2007). Genetic or biological predispositions were mentioned but not developed as they were out of scope for this work. An antecedent of happiness was considered external if the focus stemmed from outside the individual, such as the context, or conditions that they find themselves in at any given moment; this could include micro-environments such as one's immediate family environment, or macro-environments such as broad societal conditions (Diener, Oishy, et al., 2018). First, a summary of internal antecedents is offered, followed by external antecedents.

*2.2.1 Internal antecedents of happiness: individual differences*

In past studies, SWB has been identified as the result of predictors including individual differences related to genetics, personality, and demographic variables (see for example, Diener & Pressman, 2017; Diener & Lucas, 2000; Gannon & Ranzijn, 2005; Lyubomirsky, Sheldon & Schkade, 2005; Weiss, 2007). Most of the research linking SWB to personality has done so by focusing on the Big Five model (Steel et al., 2008) and has shown strong associations between personality traits and SWB along with psychological well-being (Anglim et al., 2020; Sun et al., 2018). It is important to note that within the field of well-being there are other conceptualisations (e.g., psychological well-being) which fall outside this work's scope and therefore will not be addressed. However, given the previously mentioned historical difficulty of conducting research within the field of happiness, namely due to differing definitions and conceptualisations (Anglim, et al., 2020; Diener & Choi, 2009; Deci & Ryan, 2008; Ryff & Keyes, 1995), those circumstances led to different measures being used and study's results being achieved. As such, some reported results on the connection between "happiness and personality" (for example) require careful consideration when a comparison is intended as they may have focused on different theoretical frameworks to define well-being (as well as personality). Focusing specifically on the relationship between SWB and personality traits, a comprehensive meta-analysis was conducted by Steel and colleagues (2008) which may be consulted for reference. Their findings referred to the relationships found in the literature with regards to four SWB facets (tentatively suggested based on their review), including satisfaction with life, happiness, overall affect, and quality of life (Steel et al., 2008) and personality assessed based on the five-factor model that includes the traits: extraversion, neuroticism, agreeableness, conscientiousness, openness to experience. The analysis presented by the authors showed significant correlations between all four SWB facets and all personality traits except openness to experience, which was only found to not be significantly related to life satisfaction (but significantly related to the other facets)

(Steel et al., 2008). The reported results suggest that personality measured using the big five model as the framework should predict from 39% up to 63% of the variation in SWB facets used (39% for positive affect, 63% for quality of life), which is a considerable increase compared to previous findings (e.g., DeNeve & Cooper, 1998) which place the correlations in the single-digits percentages. To further continue the discussion of the relationship between personality and SWB, researchers have determined that there is a gap in the literature concerning the use of narrow personality traits (Anglim et al., 2020; Quevedo & Abella, 2011; Marrero et al., 2016) in the intention to analyse the nuances that may underpin this relationship (Anglim et al., 2020; Anglim & O'Connor, 2019). A recent study (Sun et al., 2018) analysing the relationship between the big five model (using a 100-item Big Five Aspects Scale, DeYoung et al., 2007) and SWB found that the trait extraversion was the most strongly positively correlated to SWB, and neuroticism was showed to be the strongest negative correlation whereas the remaining three traits revealed moderate positive correlations. However, it is important to note that these results were obtained by operationalising SWB through the use of the satisfaction with life scale alone (Diener et al., 1985), which does not measure two of the three components of SWB (positive and negative affect). Another study that showed significant relationships between personality traits and SWB was Warner and Vroman's (2011), in which extraversion, agreeableness and conscientiousness showed positive correlations to practicing certain behaviours that influenced SWB. These SWB inducing behaviours included being optimistic and savouring, and those that showed the weakest links between personality and SWB were meditation and religious/spiritual behaviours. Unsurprisingly, Neuroticism negatively correlated to the same behaviours. Despite the indication that there is a genetic predisposition to happiness; the mix of personality and genes could potentially behave as a trigger — when an individual is faced with a negative situation, they would have a "reserve" of happiness that they could make use of in those times (Weiss, Bates & Luciano, 2008).

One of the most significant and consistent findings regarding the relationship between personality and happiness is that the latter changes in ways that are not a reflexion of random and temporary (unstable) factors. The affective and cognitive aspects of the relationship between personality and SWB have been shown to be consistent across both time and situation (Diener, & Lucas, 2000).

With regards to other demographic variables (such as age, gender, etc.), they have consistently been used in psychology research studies and linked to SWB scores (Tan et al., 2020). These indicators may be referred to in the literature as objective well-being measures (Voukelatou et al., 2021; Dodge et al., 2012). Examples of past findings that included these variables include Dolan et al.'s (2008) finding that age's effect on happiness is U-shaped, where people's happiness is at its highest at the youngest and oldest ages, and at its lowest during middle-age (32 to 50 years of age) in western countries, but this relationship is linear for sub-Saharan countries where care for the elderly is inexistent (Deaton & Tortora, 2015). Considering gender, the results are mixed. There have been studies that revealed that women are either happier than men or no significant differences are shown (depending on the country), regardless of their countries' economic development, women's rights, or religion (Zweig, 2015)., but it is important to note methodological limitations. In the aforementioned study, there was use of a single life satisfaction question, which is long and verbose (a total of 96 words), which asked participants to rate their agreement on a scale from zero to ten. A subsequent study by Joshanloo and Jovanović (2020) using the same poll as Zweig (2015) but across a larger span of years (2005 to 2017, versus 2005 to 2008, respectively) reported small gender differences in line with the 2015 study, however, it was able to identify that males over the age of 63 scored higher on the life satisfaction criteria, which had not been found before. These studies might have had additional methodological and analysis downsides; as reported by Montgomery (2022), when the same Gallup poll results are analysed in such a way as to account for other demographic variables (including education, country of origin, etc.), the previous findings dissipate and, in fact, men are shown to appear to have higher satisfaction with life. This 2022 used a technique called anchoring vignettes which request that participants rate themselves as well as a set of hypothetical vignettes depicting people with similar and different characteristics to their own and aim to provide a better and less biased overview of what each participant's views are with regards to a specific issue (such as life satisfaction). Montgomery proposes that the differences in female and male ratings of life satisfaction might be, in part, related to differing expectations and standards, as well as bias. In her 2022 study, Montgomery obtained participants' personal zero to ten rating on the 96-word life satisfaction item, as well as the individuals' ratings of six fictional anchoring vignettes. Upon analysing the data, she reported that on the simple average of male / female life satisfaction ratings, females rated much higher than males, however, after adjusting the models to include the results from the dataset with the vignettes (which also controls for other objective parameters such as income, education, health, etc), the difference dissipated and women's average ratings were lower than men's.

Finally, education's impact on happiness has also presented results that cause some speculation due to contradictory findings. For example, Clark and Oswald (1996) reported that life satisfaction strongly negatively related to educational attainment level which they proposed might be explained by the fact that achieving a higher degree of education might also raise the individual's aspiration targets, and therefore that might lead them to rate their satisfaction with life lower as they were still working towards their targets, albeit they might have been considerably higher than those that individuals with lower education might have considered. Contrary to this, Nikolaev (2018) used a large dataset with national panel data (from Australia) and reported that higher educated individuals report higher levels SWB when considered from a point of view of both eudemonia (finding meaning in life) and hedonism (feeling pleasure in their lives). Additionally, the author found that higher educated respondents were satisfied with life domains regarding financial aspects, employment opportunities, where they live, their local community, and children living at home, however but they reported lower levels of satisfaction when it comes to their available free time.

Previous research has proposed that the variation in SWB that might be determined by individual differences is around half of the total variation and at least 40% would be a result of intentional actions (Lyubomirsky, Sheldon & Schkade, 2005; Sheldon & Lyubomirsky, 2006). Due to the large unexplained variance of at least 40% due to intentional actions, decisions or activities, it highlights that contextual, cognitive, and behavioural factors are likely behind the remaining unexplained variance (Lent et al., 2005).

Lyubomirsky, Sheldon, and Schkade (2005) suggested that factors outside of the individual’s control have a significant impact in happiness, considering that 50% of the total variance in happiness is due to genetics, 10% due to uncontrollable circumstances, and the remaining 40% is the result of intentional activity.

### *2.2.2 External antecedents of happiness*

#### *2.2.2.1 Context and environment*

SWB has been said to be related to antecedents that are related to individual differences, as discussed above, as well as antecedents that originate outside of the individual, such as the context they are in, the situations that they encounter, and their overall life experience. However, the literature – both from a theoretical and empirical standpoint – is heavily skewed towards trait approaches (Wood & Beckmann, 2006) which has resulted in, primarily, between-subjects studies. While these are important and relevant studies, the information that they provide is incomplete as it cannot take into account the variations that occur within short timeframes (Saef et al., 2021).

Studies regarding person-ecology fit in recent years are yet another good indicator of the relevance of context (see for example Oishi, 2014; Yuki et al., 2013; Jokela et al., 2015). For example, it would imply that although the broad literature might suggest that extraverted individuals, on average, have higher levels of happiness (as discussed above), if the context and environment is secluded and quiet, an introverted person might score higher for SWB levels (Oishi et al., 2015; Lucas et al., 2008).

However, there is little to no research regarding the relationship between SWB and the momentary situational characteristics of what individuals experience in their everyday life. It has been pointed out that certain aspects of theory development (e.g., the effect of time and dynamic relationships that change over time, Fried et al., 2007) cannot be achieved without conducting research that is capable of identifying these varying and malleable changes in the reality being addressed nor without considering the within-subjects perspective (Xanthopoulou et al., 2012).

While it has been mentioned above that up to half of the variation in SWB is likely due to variables that are outside of the individual’s control (e.g., genetics, personality) suggesting that there might be “happy” and “unhappy” personalities (Costa & McCrae, 1980), there is reason to believe – through estimates of heritability – that 60% to 70% of the SWB variation might actually depend on environmental factors (Diener, Oishi, et al., 2018), indicating that there is a rather large possible proportion of happiness that could be explained and affected by factors that can be controlled.

While there has been a considerable increase in research using multilevel models that gather within subjects’ dataset, there does not appear to be any that have looked to investigate the link between the immediate experiences that individuals go through, and their SWB, particularly, the time sensitive component of the construct: affective experiences. This is a critical theoretical and methodological gap in the literature. It appears that the present work is the first instance designing studies specifically aiming to address this discrepancy.

#### *2.2.2.2 Social context and the importance of social relationships*

A part of the information that may be difficult (if not impossible) to obtain unless researchers are able to take into account relatively frequent and quick changes in certain variables. One of said variables is related to the socialisation aspects of the human experience. Particularly when leaning into the world of positive organisation scholarship, it is easy to reason that within the same work week, day, or even hour, an individual might engage in rather different interactions with others – some of a more personal others more professional nature – but in any scenario there is a vested interest in understanding these connections with others. Firstly, to understand if the relationships are positive or not, and secondly to understand whether they have a bearing on how the person feels in that moment. Having positive relationships in and out of the workplace is a focal point for our SWB (Dutton, 2003). A 2016 study by Rosales, noted that positive work relationships can improve interpersonal awareness, contribute to the enhancement of empathy, higher levels of compassion, and other positive outcomes. Overall, it is one example of a few promising empirical findings that highlight how important it is to acknowledge and understand the effect that relating to others on a daily basis has on our SWB. In the context of workplace relationships, it is important to note that some may be forged outside of the standard boundaries of the workplace. There will be instances of relationships that are formed and developed for the purpose and within the boundaries of the organisational setting, which could include, for example, mentoring or coaching relationships, developmental networks of some kind, etc. But there will also be scenarios in which friendships are forged, or while the relationship might have initially been strictly workplace-based, it may have evolved into a more personal realm (for example, this could be due to one of the parties involved leaving the organisation and therefore subsequent socialisation has to occur outside of the workplace confines). Workplace personal relationships (such as friendships) can have both positive and negative ramifications (Pillemer & Rothbard, 2018). If friendships are considered to have four main pillars that are critical for the relationship to be sustained as a friendship, these four domains would be: a) friendships are informal, b) they occur and are maintained voluntarily by the friends, c) they develop and share a set of communal norms, and d) usually they share or have similar socioemotional goals. Considering the hallmarks of the traditional workplace and its relationships it is relatively straightforward to consider that the friendship requirements and expectations mentioned above might create tension with some of the crucial elements of life within an organisational setting, which include a) having a formal role assigned to each person (usually as strict as it can be due to the presence of contracts and contractual obligations – e.g., dealing with confidential information as part of an organisational role, and not being able to share this information with a work friend since it would breach the contract and general code of conduct of the organisation), b) workplace settings tend to impose involuntary constraints on people at various levels, c) contrary to a friendship setting where the norms are communal and generally mutually agreed and pleasing, workplaces inform employees of the norms to follow, without requiring (or permitting) accommodations – therefore there are exchanged norms, and d) finally, as an employee the individual must consider and contribute to the organisations instrumental goals – even when at times they may not contribute to their personal goals or ambitions. Despite these challenges, there are also reasons to consider the advantages that a workplace friendship might bring. For example, Mao, Hsieh and Chen (2015) found that their sample of employees reported higher rates of job significance when a workplace friendship co-occurred, which could suggest that there may be motivational gains by enabling the more informal and personal to form and flourish. Similar but broader findings from Ozbek (2018) reported that having a friendship with either a colleague or a supervisor both produced desirable outcomes. In the study, their analysis revealed that there was a negative relationship between the workplace friendships (of either type) and turnover intentions as well as job insecurity, further finding that for those employees with poorer work ethic, the friendship with a supervisor, in fact, improved their performance (the same was not seen for the employees with a stronger work ethic). Interestingly, these are not linear or straightforward findings. As an example, Colbert, Bono and Purvanova (2016) established a link between the functions of a relationship, and the outcomes that are associated to the relationship. The functions of relationships included but a set of options that are more traditional and seen in research (for example, task assistance, career advancement, and emotional support) in combination with other functions (such as personal growth, friendship, and giving). Their findings revealed some unique pairings, including that the function of task assistance was more related to the outcome of job satisfaction, whereas the function of giving was most related to feelings of meaningfulness. The authors suggest that the presence of these positive workplace relationships are a suitable vehicle for flourishing in the workplace. On the other hand, research also appears to suggest that weak ties with others can bring benefits as well (see, for example, Sandstrom & Dunn, 2014a, 2014b). The concept of weak ties as implemented by the authors refers to relationships that require and rely on fewer instances of contact (i.e., someone who the individual interacts less often with), the emotional intensity is also lower than a stronger tie as these weak ties' relationships are of "lower stakes", involving less enmeshment in one's life and therefore reduced intimacy. Some of the benefits of these weaker types of connections have to do with broadening one's perspectives and obtaining information that would not normally be available within the circle of stronger ties (Granovetter, 1973). Sandstrom and Dunn, (2014a) alert to the fact that, from a methodological point of view, if an individual is asked about their recent interactions with others, in all likelihood they will be reporting on their strong ties, making it difficult to surface information and knowledge about their weak ties. From this point of view as well, an experience sampling methodology would bypass this situation, as the participants are likely to take part in the research both at times when they are interacting with others with whom they have strong ties, as well as moments in which they are engaged in a weaker tie interaction.

With the relevance of positive relationships at work, strong and weak ties alike, becoming more and more acknowledged in the literature, it stands to reason that understanding how they might relate to individual, subjective, perceptions in real-time over the course of the workdays. Identifying these patterns opens the door to the possibility of better managing workplace relationships (both at the individual as well as organisational level) and potentially offer valuable insight that could also translate into the creation of stronger, more positive, work teams.

### *2.3 Measurement of happiness*

Throughout the previous chapter, the disparity between the attention that past research has expended on causes of happiness that relate to individual differences versus those that relate to the specific experiences that people encounter was made clear. In this chapter, a discussion surrounding the measurement of happiness will continue from a methodological perspective, including making a case for the use of an experience sampling methodology (ESM) that allows real time and longitudinal data collection as panel data with continuous outcomes. Combining what has been discussed in the former two chapters, it becomes clear that the field of SWB has seen mostly: (a) cross-section studies; (b) longitudinal studies with aggregate data; (c) implementations that focus on trait-like SWB and antecedents, more so than those that are time varying; (d) a significant lack of longitudinal studies with disaggregated data; and (e) a lack of experience based studies that reflect real-time, naturalistic, depictions of SWB experiences.

In the present chapter, the focus will be on measuring SWB, its main strengths and challenges, and the methodological gaps that this thesis addresses. The first portion of the chapter will review the most discussed issues surrounding the process of measurement of SWB, starting with some known strengths and challenges in the field, followed by a description and critical analysis of the most ubiquitous measures used in studies that measure SWB. To complete the chapter, a critical overview of the case in favour of the development and use of experience sampling methodologies in SWB research to tackle major outstanding theoretical and methodological gaps in the field of occupational psychology and SWB.

#### *2.3.1 Measuring subjective well-being: key strengths, challenges, and tools*

Over the past decades, the dominating SWB measurement trend has been squarely focused on self-reported measures (Diener, Lucas, et al., 2018; Pavot, 2018; Diener, Oishi, et al., 2018). Given the nature of the construct being inherently subjective, this choice is fundamentally suitable, and it benefits from directly obtaining the respondent's rating regarding their SWB experience (Diener, Oishi, et al., 2018); when using methodologies that involve self-reports and informant reports, there is a high degree of concordance in the ratings and, when there are rating differences, the informant reports tend to be higher (Sandvik et al., 1993). This suggests that although the measures might be based on self-reports, given that they converge well with informant reports (i.e., someone who knows the individual well and provides a rating for their SWB), there is no reason to suspect gravely misleading self-assessments when it comes to SWB. The study of SWB has seen a multitude of measurements be developed and used, and for the most part, these show good psychometric properties, including reliabilities over the generally accepted level of alpha of .7 or .75 as an indicator that an instrument is reliable (Schimmack & Oishi, 2005; Pavot, 2018; Diener, Oishi, et al., 2018). For a more in-depth review of the psychometric properties of SWB measures, see for example Pavot (2018) or Lucas (2018).

A concern and criticism regarding SWB measures relates to the fact that some authors defend that extraneous factors might play a role in the self-assessment ratings of SWB, for reasons that are not related to the construct (e.g., the weather at the time of responding) (Schwarz & Clore, 1983; Deaton & Stone, 2016; Strack et al., 1988). Another difference in ratings for reasons that are unlikely to be related to the SWB construct itself was identified by Heffetz & Rabin (2013) who noticed that when attempting to contact respondents to collect their SWB ratings, there were differences between those easier or harder to reach, with harder to reach men slightly happier than easily reached male respondents, and the opposite was true for females where the most difficult to reach women had lower SWB ratings than those easily contacted.

While this criticism refers to confounding variables that should not be reflected upon survey responses, there is also the question of temporally variant factors. These could be divided into affective or mood related states, or situational or contextual factors (Pavot, 2018). On the one hand, there is value in measuring intentional varying variables to identify whether they impact SWB, and on the other hand there are several variables with the potential to affect the outcome incorrectly (e.g., mood shifts or the order that the questions are asked in). According to authors such as Dolan and Kahneman, when the attentional focus is placed on a previous experience, it is possible that it won't necessarily translate into the precise feelings experienced at the time they occurred (Dolan, 2014; Kahneman & Riis, 2005). This could potentially be related to why a person might be less likely to assess themselves as “very happy” if they recently experienced what was mostly negative affect (Diener, Lucas, et al., 2018; Kahneman & Riis, 2005).

The attempt to self-assess (with a survey or questionnaire-like tool) may be affected by social desirability biases, not being fully aware of their own SWB, being unwilling to share their true self-assessment (Diener, Lucas, et al., 2018), or by the lack of information regarding the final consequence that a past event may have if said final consequence hasn’t completely unfolded yet (Schooler, Ariely & Loewenstein, 2003). The act of asking an individual about their SWB may even potentially alter the respondent’s actual SWB (e.g., by sparking the need to consider multiple scenarios of the future outcome of a past experience) undermining the primary intention (Kahneman & Riis, 2005). Similarly, the introspection required to answer a survey about our own happiness may, in part, affect the measure itself. By focusing more on positive or negative past events while completing the survey (as necessary throughout), the assessment may differ from what was originally intended. Finally, answering a survey requires accurate retrieval of previous feelings and a good integration of the experiences had over time, which leads Kahneman and Riis (2005) to suggest that this is a possible downfall of survey-like methods for the measuring of happiness as they may be affected by memory issues or biases (Pavot, 2018), since they rely on the use of retrospective evaluation mechanisms. This limitation could be particularly critical for events very distant in the past, or for events of long duration (even if not very intense) as research shows that individuals tend to be more biased by the length of an event in their lives, rather than their intensity (Diener et al., 2009). One of the ways in which research has sought to address this limitation is by using more ecologically valid methodologies, including by combining different answers across time points into an average score. Studies have shown that these aggregated momentary SWB scores correlate highly with other self-report measures (Thomas & Diener, 1990). Despite the fact that it has long been identified that there is a need to consider time as an additional relevant dimension in assessments of SWB (e.g., Warr, 1997; Ilies, 2007), research is especially lacking with regards to within-individual fluctuations of SWB. A 2017 study by Yap and colleagues pointed out that prior studies that had attempted to investigate the transient factors and their impact on SWB relied on particularly small sample sizes (e.g., N=14 in Schwarz & Clore, 1983). Yap et al.'s (2017) investigation included a review of the total of eight studies that specifically looked into momentary mood fluctuations and their impact on SWB, highlighting that their Ns were particularly small and the fact that the methodological weakness might have overly inflated the reported effect sizes due to the small sample sizes. Their work then proceeds with a set of replication studies, as well as new conceptualisations of how to induce mood, and importantly, their nine studies involved a minimum of N=118, up to a maximum of N=461. Despite the much larger sample sizes, it is worthy of note that all these studies' participants were recruited as a convenience sample of university students. It is worth of note that in these few studies, including Yap et al. (2017), SWB was generally implemented as satisfaction with life and overall ratings of how one's life is going, whereas, by the definition, mood and affect states are not meant or expected to exhibit long-term stability. However, recent research's view on the matter has been dominated by a perspective of controlling for and accounting for momentary variations as something to be reduced or eliminated from SWB studies (Pavot, 2018), failing to acknowledge how each individual experience might be meaningful in terms of how people experience their days and the influence that these fluctuations might bring to their behaviours, interactions, decision making processes, etc. As such, a critical gap in the literature remains where there is little to no evidence on what kind of situational or contextual variables have an impact on the transient component of SWB (affect experience) as opposed to the cognitive and time-stable component (life satisfaction). While research has emphasised that picking up on momentary changes to SWB might not always be relevant, depending on the research question, there are numerous application scenarios in which this knowledge would be relevant, namely in contexts of health psychology, designing interventions aimed at improving SWB within self-contained environments (such as the workplace), and occupational psychology in general.

### *2.3.2 Measuring subjective well-being: the case for experience sampling*

To counter the challenges associated to the use of life satisfaction surveys as the ubiquitous and often exclusive tool in many studies that intended to assess happiness, Kahneman et al. (2004) emphasises that it is important to understand how people experience their daily lives (and spend their time) in order to assess it, making a case for both the Day Reconstruction Method (DRM) and Experience Sampling Methodologies (ESM). The idea behind Kahneman et al. (2004) proposed DRM was that engaging the subjects to analyse detailed information from the day before was more cost-effective and less intrusive than using an experience sampling methodology, while eliminating the unearthing of very distant past events from the study designs. Participants would be given a set of packets which included detailed instructions on how to fill out their data, a personal packet that was not sent back to the researchers, and the actual DRM assessment. Once at the end of every day, participants would go through the same procedure, beginning with a summary of their day in the form of a diary entry (not to be shared with the researchers, used for task-aiding purposes only) where they included how their time was divided and what was done at each interval, followed by a series of closed questions and ratings regarding their experience (Kahneman et al., 2004). The DRM has a number of advantages, including the reduced reliance on far-flung memories and the rather detailed overview of an individual's day, however, it also presents significant weaknesses. For example, the DRM was quite time consuming, requiring 45 to 75 minutes to complete each day, and it still relied on appropriate retrieval and good integration of previous memories, a potential downside previously mentioned, albeit to a much lower degree due to it only going back to the previous 24-hour experiences.

Experience sampling methodologies (ESM) have traditionally been regarded as invasive, time consuming, and expensive to implement (Lucas, 2018) which might have acted as a deterrent to larger numbers of researchers entering the field of SWB from an ESM perspective. ESM relies on gathering information regarding how participants feel at the moment of asking, throughout their day, rather than "how they felt yesterday" or "how they felt when they were last in a certain situation". This is achieved by prompting individuals to participate at specific moments in time (Oerlemans & Bakker, 2013; Mehl & Conner, 2013). Today, technology makes this approach much more cost effective than in the past. Historically, ESM usually required either offering the participants a form of electronic device for the single-use purpose of the research (such a PDA, in an era before smartphones were commonplace), or that the researcher made phone calls to each participant to obtain their responses and record them. Nowadays, with the advent of portable personal technology and specifically the widespread use of smartphones, the ESM can be adjusted to be convenient both for the research team and to suit the participants' lives. It no longer requires large budgets for gadgets with limited other uses, nor an enormous number of manhours to collect data; by developing ESM strategies focused on using the device that each individual will usually carry daily regardless of the ESM application – their own smartphones – ESM should no longer be regarded as an expensive and time consuming strategies significantly beyond other types of study design. In addition to this, it considerably decreases the burdens that might have been concerning in past iterations or formats of ESM. Using a mobile application for the ESM collection of data creates opportunities for design decisions that tackle the unwanted burden of a longitudinal repeated measures design. For example, the software developers could establish goalposts where the participant is not prompted more than a set number of times within a period defined by the researchers (e.g., a maximum of twice a day, or fifteen time per week, or only one prompt after 6:00pm), or that if the participant does not interact with the application for a period of a few days, the software automatically pauses notifications until the participant re-engages. There are also the aspects related to notification management, or “screen time” style of decisions that can be made. A particular study may deem that “push notifications” (i.e., the kind of notification that always show up, such as a phone call or a text message) are not necessary and instead opts for “silent notifications” – they are available on screen when the user reaches for their phone, but the phone does not emit a sound or vibration for it, avoiding distractions. Software developers are also able to develop the application such that if a user takes longer than a certain amount of time on any given interaction with the application, then they are thanked for their input and that session ends without further taking the user’s time. These are methodological and design decisions more than technical limitations. Today’s software development allows for these and other logistic management options that should make the use of a mobile application for an ESM study a very appealing alternative to more traditional research methods paths.

Previous studies have shown that certain actions may be effective in increasing happiness, and that these actions may be done in the spur of the moment. Actions such as being optimistic; worrying less; doing acts of kindness; taking care of one’s social relationships; focusing on improving flow experiences; enjoying life’s joys; committing to goals; among others (Warner & Vroman, 2011) are unlikely to be possible to access and measure without a methodology that is sensitive to quickly changing scenarios, such as ESM. Since actions with the potential to influence positively happiness are likely done out of instinct, necessity, or adaptation to the context, and not a carefully planned out behaviour, their impact may be more easily forgotten. Traditional measures used in Psychology are frequently constructed and applied in ways that don't capture these sorts of actions and mechanisms, for the various reasons already mentioned. ESMs can be used to tackle the major theoretical and methodological literature gap mentioned before – the almost complete lack of empirical research on the situational antecedents of SWB. As this type of research demands the use of a methodology that has the capability to identify malleable changes in individuals' everyday reality to understand the within-subjects perspective (Xanthopoulou et al., 2012), it is important not only to assess how one's affective experience varies throughout the day, but also what other contextual or social variables fluctuate with it. While following an ESM procedure might not be sufficient to establish a solid causal effect, it is a step in the right direction by exposing which relationships are present and require further experimentation.

The application of such a methodological improvement has immense potential in the field of occupational psychology in general, and SWB studies in particular. For example, in the context of SWB at work, it is key to understand what potential controllable factors have an impact on employee well-being. This kind of knowledge would afford organisations more reliable decision-making models, the development of more effective positive psychology interventions directed toward improving organisational or individual well-being, and a deeper, fuller, understanding of the human experience of employees to better address their individual needs.

### *2.4 Workplace happiness*

This chapter focuses on the knowledge and empirical evidence that explains the relationship between happiness and organisational contexts. First, a comprehensive overview of the findings surrounding SWB in the workplace will be provided, followed by two subsections pertaining to productivity: in-role and extra-role performance. The first refers to performance of tasks or obligations that are inherently expected of someone due to their job and explicit responsibilities within the company or the working team. In-role performance is usually prescribed by the organisation to the individual and includes all common and uncommon tasks that directly relate to one's job or position. On the other hand, the literature surrounding extra-role performance will be discussed; this type of performance is associated to the pursuit of desirable citizenship behaviours through tasks or activities that are generally optional in nature and are not prescribed by the organisation, often referred to as organisational citizenship behaviours (Sattar et al., 2017).

The existing literature suggests that being happy at work yields positive outcomes for the organisation (Field & Buitendach, 2011; Fisher, 2010; Gavin & Mason, 2004; Money et al., 2008), although this research path is still rather limited (Oswald et al. 2015). Two of the positive organisational outcomes frequently mentioned in the literature as a result of higher employee SWB are productivity and business unit profitability (Harter, et al., 2010; Harter, Schmidt, & Hayes, 2002). A suspected but cautious causal link between SWB and organisational outcomes has been suggested by Diener, Lucas, et al. (2018) who the presence of a link between SWB and higher productivity and citizenship behaviours, improved creativity, and self-regulation. Previous studies have shown that employees with higher levels of job satisfaction (Riketta, 2008; Boehm & Lyubomirsky, 2008) and positive affect (Oswald et al., 2009; Wright & Staw, 1999; George, 1995) perform better, and those with higher happiness levels have a higher chance of being re-employed after unemployment (Krause, 2013). At the organisational rather than individual level, there have also been interesting findings in empirical studies, along the same lines as the individual level performance findings. Multiple desirable organisational outcomes such as sales, share prices, productivity, reduced turnover, and customer loyalty have been linked to measures of SWB (e.g., Edmans, 2011; Böckerman & Ilmakunnas, 2012; Rusbult & Farrell, 1983;

Harer et al., 2010). Personal level outcomes such as earning higher wages and professional competence were predicted via SWB studies (e.g., DeNeve & Oswald, 2012; Kansky et al., 2015).

One of the ways in which authors have investigated the effects of SWB regarding positive work outcomes is how individuals perceive their work, their experience of work, and how work sits within their belief and attitudes systems. Traditionally, work was seen as a means to an end — an endeavour that is necessary, serving a purpose. This remains the case even for individuals who don't extract particularly positive feelings or experiences from their work, as well as for those who don't believe their work to be meaningful. SWB affects how individuals allocate their time to various activities, opting for spending more time on interesting tasks (Oswald et al., 2015), suggesting perhaps there should be a noticeable relationship between the task(s) being performed, and the positive affect experienced by the individual at that time. Another facet of how individuals perceive work is meaning. The idea of work having meaning goes beyond the financial dimensions associated with it (Steger et al., 2012; Rosso et al., 2010). An individual can experience meaning regarding their work to various degrees, depending on both the meaning of the work itself and the psychological meaningfulness derived from it. The first refers to how important the experience of work is (work as a "job" vs "career" vs "calling"), while the second has to do with the closeness between one's self-concept and their work role (van Zyl et al., 2010). Research indicates that, where meaning is concerned, those who consider their work to be a "calling" are happier than both those who believe their work is a "career" or a "job", and those who consider their work as a "career" are still happier than those who see it as a "job" (Dik & Duffy, 2007; Peterson et al., 2009, van Zyl et al., 2010).

Before continuing to specifically discuss performance and productivity's relationship with SWB, a note to mention that in line with had been noted earlier with regards to the studies and empirical evidence provided throughout this thesis, the studies that have generally been conducted as part of occupational psychology research are also primarily cross-sectional, with distinct and varied operationalisations of the construct of SWB – at times as job satisfaction, and much less commonly as other implementations. However, specifically regarding occupational psychology studies, it is worth noting that although satisfaction is one of the words that is often interchanged with SWB, a recent study (Joo & Lee, 2017) has confirmed that career satisfaction is, in fact, different from SWB and that career satisfaction fully mediates the relationship between satisfaction and SWB.

Another popular topic in occupational psychology literature is engagement. This is a topic often referred to in conjunction with SWB as the cause for certain organisational gains and improvements. However, it has been suggested that engagement could be one of various happiness components (Peterson & Seligman, 2004, Money, Hillenbrand & Da Camara, 2008), akin to activation (i.e., as if being engaged were to signify that the individual has activated affective responses, for example). A 2011 study by Field and Buitendach, showed a relatively low correlation between SWB and engagement ($r$ = 0.27), further supporting the view that these are indeed separate factors, and should be measured separately. Engagement in the workplace is outside of this thesis' scope and therefore will not be addressed beyond this note meant to clarify a common combination of factors present in occupational psychology.

#### *2.4.1 In-role performance (prescribed)*

It is in the best interest of organisations to have happy employees; Myers & Diener (1997) point out that these are the workers who invest effort and excel at their job. Happy employees tend to show higher levels of productivity and creativity both in terms of tasks as well as alternative solution-finding to improve effectiveness (Saenghiran, 2014). Studies have shown that some of the positive outcomes that stem from working with employees who are affectively committed (Ammari et al 2017; Abdallah et al., 2017) include increased effort and performance ratings, as well as desirable and innovative employee behaviour (López-Cabarcos et al., 2015). Unhappy workers, on the other hand, are more likely to miss days of work or to leave the organisation altogether (Tenney et al., 2016).

Despite these promising results, the relationship between SWB and productivity is not straightforward, and effects may not be as large as might be initially suspected (Tenney et al., 2016; Riketta, 2008). Wagner and Heatherton (2013) noted that negative affect is one of the strongest threats to self-determination and accomplishing one's goals by masking the realistic scenario one is in and decreasing awareness of the person is on track to achieve what they set out to do. This highlights the need for this relationship to receive further consideration (Tenney et al., 2016), and possibly a re-evaluation, regarding how the various constructs are implemented, since many of the existing studies measure productivity as well as SWB differently. Other authors have found that improving attentional focus on work tasks correlates to higher productivity (Toniolo-Barrios & Pitt, 2021; Lai et al., 2020), which could relate to the state of flow, which has been linked to positive emotions and feelings (Csikszentmihalyi & Csikszentmihalyi, 2014).

#### *2.4.2 Extra-role performance (desirable)*

The literature pertaining to happiness and extra-role performance (or organisational citizenship behaviours) is challenging in the sense that there are no definitive take-aways yet (Tenney et al., 2016). As identified above, extra-role performance is related to organisational citizenship behaviours; meaning, non-prescriptive behaviours that aim at helping others in the workplace (Sonnentag, 2015). Research has previously established that the likelihood of helping others is tied to the experience of positive affect (Miles et al., 2002), which is beneficial to the organisation (Magnier-Watanabe et al., 2017). It stands to reason, that it might be beneficial for a company to enable the formation of social relationships within the workplace to reap rewards in different ways. Pettigrew (1998) pointed out that even for issues as complicated as organisational change, learning about the group, promoting behavioural change, and encouraging the development of friendships generates positive feelings, which are likely to generalise towards the overall group, successfully navigate change processes.

Some authors suggest that increased levels of SWB may be better predictors of tasks that have a social component (e.g., making a good impression on someone) or to handle highly complex tasks. The implication of such a perspective is that focusing on strategies meant to increase SWB may not translate into an immediate performance or productivity improvement concerning a given cognitive tasks of average complexity (Tenney et al., 2016; Oswald et al., 2015). Studies have also found that induced positive mood was associated to higher collaboration and joint goal achievement (Carnevale & Isen, 1986; Brooks, 2014).

## Chapter 3: Research Design and Methodology

### *3.1 Rationale for the longitudinal study design*

Research into subjective well-being has simultaneously focused heavily on the cognitive component of the tripartite SWB framework, and it has been overwhelmingly investigated with cross-sectional designs. There is limited knowledge on the usability and applied benefits of measuring real-time data in relation to its relative challenges or weaknesses as a consequence. Due to the relatively sparse literature that has employed this style of research design there is a possibility that our existing psychological models, predictions, and even interventions might have a blind spot. For example, if real-time data is able to identify statistically significant patterns in relation to the antecedents of subjective affective well-being, that should equip organisations to make more meaningful positive changes to the environment they offer their employees. Similarly, if this longitudinal and real-time data collection approach proves viable and suitable, it will be a good starting point to deepen this perspective by, for example, looking more closely into the effects that the affective experiences produce both on individuals themselves, as well as those around them, to what degree, and in what ways.

Previous longitudinal studies have found slightly surprising – or not fully explained – results. In 2016, Wettstein et al.  reported that while objective SWB indicators verified during a five-year span all declined in that period, the same was not true for the subjective parameters. Interestingly, they also discussed the fact that their predictive ability was low when relying on objective functioning indicators (even those that were time-varying) to determine future SWB, which is an interesting perspective that raises questions about the need to more consistently investigate the relationship between the affective component of SWB and the contextual and social elements that characterise most people's everyday lives. This study's results suggest the need for caution prior to producing generalisations or to extrapolate the findings, since the sample was small (N = 124), and the sample was entirely made up of elderly participants (ages between eighty-seven and ninety-seven years old). Additionally, as this study resorted to secondary data analysis from the data poll collected as part of the LateLine longitudinal project (Neubauer, Schilling, & Wahl, 2015; Schilling, Wahl, & Reidick, 2013; Wettstein et al., 2015), the sample only include these older-than average individuals who also met the criteria of living alone. Whilst this may indicate physical and cognitive health, in the sense that they are able to care for themselves safely, it may also hide a dark side. It is known that elderly people are susceptible to loneliness (Domènech-Abella et al., 2017), and while living alone does not discount the possibility that these participants might have a healthy and fulfilled social network outside of the home, it should be considered as having potentially affected the quality of the findings.

More recently, Hansen and Blekesaune (2022) investigated the longitudinal relationship between aging individuals and their SWB. The premise being that should it be sufficient to refer to biological or individual differences parameters (e.g., sex, income, etc.) to predict the SWB pattern as a person ages, it would be expected to see a steady decline of SWB the older the person becomes. However, in their study of nearly five thousand individuals (aged forty-four to ninety-five), they did not find the pronounced SWB decline with age that may have been anticipated – instead, they report a relative stability into old age. The authors also report that the most noticeable SWB decline happens in the cognitive component of subjective well-being (life satisfaction), rather the affect experiences. Crucially, this is an indication it is not sufficient to implement objective and cross-sectional methodologies to understand and obtain the complete picture.

By definition, a longitudinal design also sets the foundations to create the conditions to establish causality (Taris & Kompier, 2014). While this is not intended to mean that it is “better” than other methodologies, it does afford a data-richness that simply is not possible with the more frequent cross-sectional designs. Amongst the limitations that are often seen with longitudinal studies, the appropriate design along with the practical challenges or higher demands that it entails are frequently listed. Nowadays, with the advent of technology and specifically the widespread access to it some of these logistics' barriers have reduced. Nonetheless, one must keep their bias in check and it needs to be acknowledged that if access to technology (particularly personal technology, such as any type of expensive device – e.g., smartphone, unlimited data plans to enable consistent and reliable access to the internet, etc) is a core requirement to obtain participant data, there will be certain important groups of society that will be excluded without a possibility to pursue an alternative means of participating, even if they had the desire to do so. This could include lower socio-economic status groups, certain communities with lower rates of adoption of technological advancements (e.g., elderly populations, disabilities that negate the use of certain devices due to their design, etc.). As such, while there is a great need for longitudinal designs in psychological research and specifically within the field of SWB, it should not be seen as a perfect solution. As with other design and methodological option, this too comes with advantages and disadvantages.

## ***3.2 Experience sampling as a research method***

### *3.2.1 Experience sampling mobile application design and development*

This was an experience sampling longitudinal and multilevel study with panel data across two levels, with within and between subjects' variation. Level one corresponds to the happiness data in the form of affective experiences and this data is nested into participants (level two).

When developing the mobile app, it was crucial to consider the process that a participant would go through whilst sharing their data by participating in this research. For this reason, the software-related app development was entrusted to an experience software engineer with considerable experience in the field of data privacy and computational needs. A key requirement was to ensure that no personal identifiable information was collected at any stage (e.g., IP addresses or phone model or operating system information). Once that was ensured, the app would then include a section to collect demographic information, and every participant's data was fully anonymised at the source. The studies did not gather any data that could provide identifiable data points at any stage.

Given the intention to collected participant data over a prolonged period of time, it was important to ensure that the app was easy and pleasant to use, and that the participants would be able to complete their set of questions in each session quickly. For this reason, it was decided that after a period of two minutes within the app, when the participant tapped the "next" button, they would be greeted with a "thank you" message rather than more items to respond to. The cut-off time of two minutes was decided based on an informal pilot study with approximately 15 users and after monitoring the average times that it required users to go through a standard set of items. The "thank you" screen was tailored such that, to the participants' knowledge and perception, they were not at fault in any way, they were simply finished with that instance of the task to ensure that they did not feel discouraged to return to the study in a future opportunity.

From a point of user engagement, additional measures were implemented to minimise disruption to the participants' lives. These measures included asking the participants, when they first joined the cohort, when their usual "sleep" versus "awake" times are, such that the app would never trigger notifications during their usual rest periods. This was done so to acknowledge both the importance of quality rest in one's subjective well-being, as well as the fact that people may not all live according to the same schedule – while some participants may be early risers who end their day earlier, others may opt (or need to) awake later in the day, and stay awake into a later hour in the evening, for example, as would be the case for anyone working shifts. Another measure introduced to the app was the complete stopping of notifications should the participant not engage for more than seven consecutive days (i.e., if the participant did not open the app). In those cases, on the eighth day, the app would no longer prompt the participant to share their data until a future time when they voluntarily re-engaged with the app, which would then enable notifications to be prompted once more.

The study did not offer participants the possibility for monetary compensation, and they were free to exit the research at any point. If the participants wished their data to be removed from the dataset, they were given instructions on how to retrieve an alpha-numeric identifier, which was randomly generated upon their first contribution to the study and in no way identified them personally, and they were able to contact the researcher to have their dataset removed from the analysis. While there was no compensation associated to the study, participants were given access to the information that their total (individual) data translated to, intended as a brief overview of their affective subjective well-being, as well as the categories that they most frequently selected when their scores were at the lowest and at the highest. Given that this information was meant to be a brief summary, and in no way meant to be interpreted as a diagnosis or deterministic outcomes, this was only offered to participants once they had offered a minimum of approximately one month of data, calculated as twenty-two days to match with the usual employment calculations of what a “month” equates to in working days.

### *3.2.2 Data collection*

These studies received ethical approval from the UCL Division of Psychology and Language sciences with the number CEHP/2017/560. Given the nature of the longitudinal experience sampling strategy, the data collection occurred simultaneously for all studies.

Data was collected from adult participants, with various occupations, from around the world, who voluntarily downloaded the ESM mobile application responsible for the data collection in this study, which will be further described below. Data collection was on going from March 2018 until March 2020, when data collection was interrupted due to the restrictions imposed by the COVID-19 pandemic to ensure that the data would not be affected by confounding variables related to the alterations brought on by the pandemic. Participants could be eligible for more than one of the studies presented in this thesis, should they have provided the relevant data (i.e., responded to the necessary questionnaires) and their data was categorised in relevant groups (e.g., for studies 2 and 3, the participants would have to provide work related data – more information is specified below).

During the longitudinal data collection, the app was designed to ask participants for different types of information depending on context – which was embedded into the app's engineering. As such, there were three types of questions that the participants provided data points on:

- Single answer: there would be questions that were only required to be answered once due to their time-stable (or unvarying) nature. This could include, for example, demographic information, personality instruments, broad data about their career (e.g., stage of their career).
- Systematic: these were the questions that were asked every time that the participant engaged with the study, and they included categorical data on what the participants were doing as well as how they felt in that moment. Details about the instruments and validated scales are offered below.
- Context-depending branching: these data points refer to those questions that are only relevant if the participants prior response prompts them. For example, if the participant states that they are not working, it could not be contextually appropriate to attempt to experience sample work related elements (e.g., the type of work task being completed).

### *3.3 Materials, scales, and measures*

The studies reported on in the upcoming sections of the thesis used multiple instruments and validated measures, which are reported and described below.

As for the single-occurrence measures and metrics, these included:

**Demographic information.** All participants were asked to provide demographic data when they first joined the study. The information collected was optional (i.e., the participants were able to not offer a particular data point if they wished), and it included: age, gender, highest level of completed education, type of employment (full-time, part-time, self-employed), income, type of organisation that employees them (public, private, etc.), their current position (entry level, mid-level manager or non-manager, etc.), and number of years of professional experience.

**Big Five Inventory-10 (BFI-10):** a 10-item scale, shortened from the original BFI-44 (Rammstedt & John, 2007), was chosen due to its reduced time requirements, an important factor for an ESM app. This scale uses items such as "I see myself as someone who … tends to be lazy" rated in a 5-point scale.

**Measure of Entrepreneurial Talents and Beliefs (META):** 20-item scale (Ahmetoglu and Chamorro-Premuzic, 2010), shortened from the original 90 items. This scale measures behavioural traits across three work domains: how an individual generates, executes, and leads innovation within an organisational context. The participants are asked to use a 5-point likert scale to rate sentences such as: "*My ambition is to change this world*", "*I don't always grab the opportunities that I have*", or "*I prefer old-fashioned methods—because they work*".

When it comes to the information that was requested each time that the participant engaged with the research, it included contextual information about their activities and who they were with and the scale of positive and negative experience (Diener, Wirtz, et al., 2010; described below). The contextual information was always asked first after receiving a prompt and opening the app and was presented as: "What are you currently doing?" and "Who are you interacting with now?". These were closed, categorical, items.

**Activity.** The response options for first question, the activity prompt, included items for the following categories, which were loosely based on the categories included by Kahneman et al. (2004) in the Day Reconstruction Method (DRM): “working”, “at home”, “commuting”, “relaxing”, “caring for my children”, “leisure activity”, “other (specify)”. Categories “working”, “at home”, and “leisure activity” triggered a follow up question where participants could provide further details from a set list of options (e.g., for “work” it could include “meetings”, “doing a task I do frequently”, etc.; for “leisure” it could include categories such as “watching TV”, “out for a meal”, “holiday”, and “at home” could include tasks such as “doing chores”, “resting”, or “reading”, etc.). When it was the case that participants selected an option with a follow up item, the follow up would be specific to their initial choice – for further granularity and clarification. The options given for someone reporting to be working at this stage included: calls, meetings, usual tasks, unusual tasks, taking a break, or procrastinating. The categories were kept intentionally broad. This was done with the view of allowing ease of self-categorisation by the participants and to prevent individuals from becoming too focused on semantics or slight nuances in the wording. These categories were created following loose inspiration from the tasks referenced in the DRM (“Day Reconstruction Method”, Kahneman et al., 2004).

**Social interaction.** For the social interaction category, participants could select from a list that included various types of relationships (e.g., alone, with a partner, children, friends, supervisor or manager, clients, etc.). Similarly to the work tasks mentioned above, social interactions allowed the participant to specify who they were with. The responses were categorised into four groups: “being alone”; “being with only people with whom a personal relationship exists”; “being with people with whom only a professional relationship exists”; and “being with people with whom both a personal and professional relationship exists”. While the answers were more granular (e.g., “friend”, “family member”, “co-worker”, etc.), this item allowed multiple selections, enabling the combination of selections to be converted into one of the categories for analysis. A methodological note: this item did not allow participants to specify if all the persons selected (e.g., "friend" plus "manager") were physically present, physically distant, or a combination. This study was designed and conducted almost in its entirety prior to the COVID-19 pandemic which meant that, at the time of planning and designing, remote working was not as ubiquitous as it is presently, and while it was considered, it was deemed not to be overly important to warrant an extra layer of complexity to be added to the ESM methodology and mobile app.

**Scale of Positive and Negative Experience (SPANE)**: this is a 12-item scale that reports a range of positive (6 items) and negative (6 items) feelings and experiences that bypasses culturally specific interpretations by using simple and encompassing naming (Diener, Wirtz, et al., 2010). This scale was developed, partially, to tackle some of the criticisms received by the PANAS scale (Watson et al., 1988) which included the lack of representation of the construct of happiness through its items (Egloff, 1998), namely due to its items including both high activation and low activation components (e.g., joyful and calm, respectively) which have been reported to be indicative of structural heterogeneity (Flores-Kanter et al., 2021), and some studies having reported the possibility of a third factor besides positive and negative affect (for more on this topic see, for example, Nolla et al., 2014 or Vera-Villarroel et al., 2017). The responses in SPANE, however, are based on how much the feelings are experienced, and it has been demonstrated that this scale adds variance when comparing to PANAS' ability to explain well-being (Jovanović, 2015), and therefore it was a more appropriate choice for the present research. In SPANE, the feelings and experiences include items such as "*Good*", "*Bad*", "*Angry*", "*Content*" which are easier to comprehend, and less encumbered by culture-specific bias, which further adds to its choice as the instrument to assess the affective experiences that constitute part of the SWB definition (Diener et al., 2010). For this research, an additional negative item was incorporated as “tired” since the field of occupational psychology often considers factors such as burnout, rest and recuperation, resilience, etc., as meaningful workplace factors.

### *3.4 Participant recruitment and selection*

Sampling was done via probability sampling and subsequently using the snowballing methodology where participants and/or general population individuals who came across the study share the study with others. Any person over the age of eighteen could self-select to participate, should they wish to do so, by downloading the free experience sampling app from the official app stores on their smartphones (either the App Store for iPhone users, or Google Playstore for Android users), reading the participant information sheet, and confirming their consent to partake.

Since the primary goal of this study was to investigate longitudinal changes, a decision was made to remove participants who had fewer than five individual data-points or four elapsed days between their first and last responses. This was done with the goal of eliminating what might have been “snapshots of time” rather than a longitudinal view of someone’s experiences, as past studies have demonstrated that the distinction between self-reported affect experiences within short versus longer periods produces different findings (Flores-Kanter et al., 2021).

In total, 312 participants entered the study. With the exclusion criteria set out above, 120 participants and all of their data were removed from the dataset. After exclusions, we retained 192 individuals for analysis. Their inclusion in each of the studies is described below in the following sections which are study-specific.

#### *3.4.1 Participant selection – study 1*

Data from the entirety of the 192 participants remaining after implementing the exclusion criteria described above was included with no further exclusions and produced a total of 6,397 observations. Out of N=192 participants (102 females, 67 males, and 1 chose not to respond), the ages ranged from 18 to 55 years old (*M*=32, *SD*=8.82). These participants represented a total of 27 nationalities with 52.35% from European countries (15.88% Portugal, 12.94% Great Britain, and 11.76% Spain, 11.77% others), 12.94% identified Asian origins (10% China, 2.94% others), 17.06% South and North American, and an additional 17.65% did not answer.

The sample includes 18 people (10.59%) who reported being self-employed, which we will consider as entrepreneurs on the basis that they reported that this was their main professional occupation and as a result, this information indicates that they are not under someone else's employment, and 125 people (73.53%) reported any other type of employment situation (which will be considered as non-entrepreneurs). Despite the discrepancy in numbers of participants belonging to the entrepreneur (18 people) or non-entrepreneur category (125 people), the entrepreneurs alone provided nearly 500 responses, for an average of more than 26 (*SD*=36.62) responses per person (minimum 6, maximum 152). Their responses spanned an average of 69.11 days (*SD*=88,73), with more than half (55.56%) having participated for longer than 1 working month (27 days or more). 29 participants (17.06%) are either unemployed (4; 2.35%) or full-time students (23; 13.53%). Most of the participants indicated that they are currently In full-time employment (67.65%), whereas 11.76% responded that their occupation is part-time or studying (17.06%). A large part of the sample identifies as holding a senior (38.24%) or mid-level (31.76%) position at their current workplace, versus 10% who consider themselves to be at an entry level stage.

#### *3.4.2 Participant selection – study 2*

Since the primary goal of the present study was to investigate longitudinal changes with regards to happiness at work, a decision was made to remove datasets according to the following criteria:

a) data that was not collected while at work was removed from the analysis as the primary goal of this study is to examine whether the eviornmental and social elements experienced while at work produced significant changes in individuals momentary affective experiences;

b) participants who had fewer than five individual data-points or a minimum of four elapsed calendar days between their first and last responses were removed. The intention of applying this criteria was to further assure the true longitudinal nature of the data of at least one working week, eliminating the possibility of conflating longitudinal (of those who truly participated over a perior of at least one week) and cross-sectional data (of those who participated once, or over a very short period of time).

This process of data exclusion ensured that all data being analysed refers to working experiences. In total, 312 participants entered the study. With the exclusion criteria set out above, 201 participants and all of their data were removed from the dataset. After exclusions, we retained 111 individuals for analysis who generated a total of 1,855 observations or data points. The participants' age ranged between 19 and 75 years old ($M_{age}$= 36.14, $SD_{age}$= 8.04), and it includes 59 females and 52 males.

#### *3.4.3 Participant selection – study 3*

The same participants that were selected for study two were included in study three. As a result, the same 111 individuals' data was kept for analysis, and all of the 1,855 data points.

### ***3.5 Procedure***

Participants downloaded the experience sampling mobile app from their country's official app store. Samples of the app's screens can be seen in Appendices A through E. Once they opened the app on their devices, they were asked for permission to receive notifications and the initial screen displayed an informed consent confirmation page. This page included relevant information about the study, how to contact the researcher, and what to do if they wished to stop contributing or to withdraw their data. It was only possible to progress and/or use the app after confirming their agreement. Participants were urged to never interact with the app in any situations that might put them or others in danger (e.g., while driving), nor to feel pressured to respond immediately if the notification arrived at an inconvenient time (e.g., caring for their children, or during a work meeting). During the first interaction with the app and following the informed consent acknowledgement, participants were asked to establish relevant logistic settings. These included which times they were usually awake to ensure that they would not be disturbed during their usual rest times, as well as how frequently they were willing to be notified (a minimum of three days per week, up to seven days per week). Each day when notifications were triggered (based on the frequency that the user selected before, and could adjust later if they wished), users would be notified at two random moments of the day (within their permitted window of time). These times were truly randomised, i.e., no constraints were set in the software code other than to avoid the notifications being sent in the same hour. Participants were informed that since the prompts were sent at random times, they could still respond even if they did not see the notification immediately, and in that case, they should still answer with regards to what they were doing at the time of interacting with the app, and not at the time the notification was sent. This was meant to avoid participants falling into a past-report mechanism that involves memory recall.

Next, participants were asked to provide demographic information (per materials section above) and fill out the personality tests. Since the personality measures refer to traits rather than states, participants were only asked to respond to the BFI-10 and META once, at the beginning of the study. Following this, participants would be asked to identify what their present situation was in relation to what they were doing, and who they were with. After selecting their responses, participants were thanked for their time and informed that the app would trigger a new notification when they were due to provide responses again. Prompts were programmed to be randomly distributed throughout the days, with two prompts a day during the set periods, per person.

Users were informed that as their contributions built, they would be given access to a summary of their personal responses' after approximately four weeks' worth of data. This was offered freely to any user who inputted sufficient data to enable computation of the outputs, and it would continue to update itself as the user provided additional data. If a participant chose to stop responding (whether by deleting the app, or simply by not engaging with it), the programming was such that the app would cease sending user notifications to complete the surveys after five consecutive days of inactivity. This was intended as a courtesy to users who might have opted to keep the app installed on their phones hoping the re-join the study at a later date, but were unable to continue engaging with the app at that time.

### *3.6 Statistical Analysis*

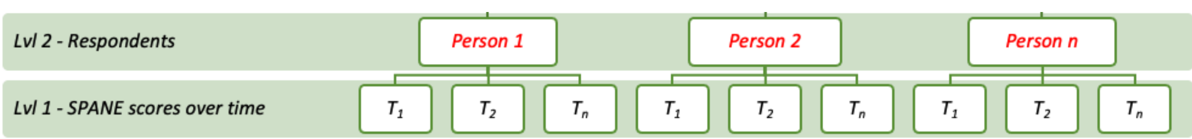
Often, longitudinal studies in psychology opt for grouping observations. In these instances, there are two main types of approaches to data analysis. One is to average all responses by the same participant to obtain one workable value per variable (see Killingsworth, 2021 for an example). Another approach that has been useful in studies where only two time periods are implemented (e.g., before and after an intervention) is to assess the relationship between the two observations (see Kunzmann et al., 2000 for an example). Given the nature of former datasets and past constraints surrounding data gathering (e.g., the widespread use of smartphones is relatively recent, and cannot be presumed for all populations), these choices would have been justified. The present study, however, collected longitudinal and real-time (i.e., in the moment) data from participants. A study with comparable momentary SWB data was published recently, where the authors analysed their data by averaging each participant's multiple responses into a single aggregate value so that traditional regressions and correlations could be computed (Killingsworth, 2021). Given that their explicit intention was to compare their findings with a relevant former study, that partially explains the reason behind the researchers' choice, despite it signifying a remarkable intentional loss of data richness.

The current study's design is longitudinal with hierarchical real-time data, which is variable both within and between groups. The variability in the data can be looked at from two points of view: a) variability over time around one's own average (time-variant person-specific), and b) variability around the overall average (time-invariant person-specific variability).

Hierarchical data structures (figure 2) are composed of observations that are correlated given that they represent different measures belonging to the same entity (e.g., the same person providing multiple answers to the same question). Due to the characteristics of hierarchical data, there is non-independence in this type of datasets (i.e., the error terms are correlated as the panel units are individuals). Independence between observations is a necessary assumption when using standard and frequently used regression techniques, such as the standard OLS regression. To account for both unobserved heterogeneity (that could be both unpredictable and/or unmeasurable) and the correlation between observations, multilevel modelling (MLM) analysis techniques are the most widespread option (McNeish, Stapleton, & Silverman, 2017).

**Figure 2**

*Two-level multilevel hierarchical data structure*




There are several multilevel modelling (MLM) analysis techniques that account for the characteristics of the dataset in use, including fixed effects (FE), random effects (RE), mixed, or hierarchical models (Rabe-Hesketh & Skrondal, 2012). Given the study's aims of determining the impact of time varying variables (e.g., situational context, interaction with others) on the dependent variable (measured by SPANE, Diener, Wirtz, et al., 2010), Fixed Effects (FE) or Random Effects (RE) models may be appropriate to use (Baltagi, 2008). Hausman tests were used to determine whether fixed or random effects models were best suited to the data in each model (Wooldridge, 2010).

*Fixed Effects (FE) models* assess the relationship between outcome variables and their predictors within an entity (e.g., person, workplace, etc.). These models acknowledge and address the fact that an entity has certain characteristics with the potential to influence the predictor variables (e.g., belonging to a minority group in a particular company or field may impact one's experience of company-wide social functions). The use of FE models accepts that these characteristics are present within the dataset and may or may not affect the outcomes. It assumes that there is a correlation between the predictor variables and the entity's error term. In short, if there are characteristics that are unobserved (or difficult to measure) that do not change over time, it is reasonable to assume that within group changes to the outcome variable must be due to other factors, since these characteristics were unchanged throughout the measurement times (Stock & Watson, 2003).

*Random Effects (RE) Models for Continuous Outcomes* addresses the naturally occurring heterogeneity between observations in hierarchical data. The heterogeneity is represented in relation to changes in the responses (Y) when there are recorded changes in the variables of interest (X). Simultaneously, the changes in responses (Y) are handled such that the known correlation to one another is accounted for, due to their hierarchical structure (i.e., multiple responses to the same question by the same participant).

The heterogeneity in the data can be observed or unobserved. Observed heterogeneity refers to differences that can be measured or controlled for in the regression model (e.g., age; gender; education; etc.). Unobserved heterogeneity includes anything that is fundamentally unmeasurable, difficult to measure, or absent from the dataset – this is referred to as residuals and it affects the outcomes; the unobserved heterogeneity factors are termed random effects. In short, this approach allows us to control for variables that cannot be measured or observed (e.g., cultural factors; difference in business practices across companies; national policies; etc.).

MLM models will be used to account for and handle the dependence of observations and the unknown (or unmeasurable) portion of the effects of potential relationships within the data. Each instance of responses will be considered as part of a hierarchical data structure grouped at the participant level. It is expected that in most cases, the random effects model will be the preferred option after running a confirmatory Hausman test as mentioned above. As such, the standard null hypothesis RE model with only a random intercept (but no random slope) is:

$$y_{ij} = b_0 + u_j + e_{ij}$$

Where the response at moment *I* for person *j* ($y_{ij}$) results from the sum of the overall mean ($b_0$ – intercept; the systematic part), and the group-specific variation around the intercept and lower-level residuals ($u_j + e_{ij}$ – the random part of the model). This model can be extended by adding covariates:

$$y_{ij} = b_0 + b_1x_{ij} + u_j + e_{ij}$$

Where covariates ($b_1x_{ij}$) can be time invariant or time-varying. In this model, the slope ($b_1$) does not vary across groups, as it represents the average slope of the relationship between X-Y. The fixed part of the model ($b_0 + b_1$) describes the population average response of Y ($b_0$) and how it changes over the value of the covariates ($b_1$).

# Chapter 4: Study 1: Momentary happiness as an outcome of individual differences

## *4.1 Introduction*

In past studies, individual differences have been found to be significant predictors of subjective well-being (SWB) (e.g., Diener & Lucas, 2000; Gannon & Ranzijn, 2005; Lyubomirsky, Sheldon & Schkade, 2005; Weiss, 2007). It has been suggested that up to half of the variation in SWB is likely determined by individual differences (including certain demographics such as age and gender, as well as personality) and the remaining proportion largely explained by other variables (Gatt et al., 2014; Lyubomirsky, Sheldon & Schkade, 2005; Sheldon & Lyubomirsky, 2006), such as intentional actions, context, or environment factors (Lent et al., 2005). SWB is a multidimensional construct which includes stable as well as malleable components. Although correlations have been found between the components, the cognitive component (i.e., life satisfaction) has a degree of temporal stability (Carrillo et al., 2021), while the affective component (i.e., experiences of positive and negative affect) is malleable and reflects the many experiences individuals go through. This has led to many instances of authors recommending that cognitive and affective SWB components should be measured separately (Carrillo et al., 2021; Lucas et al. 1996; Pavot & Diener 2008). The idea that affect is related to personality is not new. Historically, the connection between personality traits such as extraversion and neuroticism has been consistently linked to positive and negative affect (Costa & McCrae, 1980; Fleeson et al., 2002; Steel & Ones, 2002; Kardum, 1998; Mroczek & Almeida, 2004). The theoretical link between the concepts of personality and SWB has led to the belief that the former strongly relates to and predicts long-term SWB (Steel et al., 2008). Affective experience being considerably more malleable than life satisfaction (Kuykendall, et al., 2015; Lyubomirsky, et al., 2005; Sheldon & Lyubomirsky, 2006), raises the question of whether it may shift, adapt, and change frequently enough such that methodologies and instruments that focus on constructs known to be significantly more stable in time might not fully encapsulate the richness of everyday experiences. Past studies, including very recent ones, have principally looked at cross-sectional data and standard correlation and regression tests (Carrillo, 2021), and few have used longitudinal designs (Pinquart & Schindler, 2009; Kuykendall, et al., 2015) with multilevel longitudinal data analysis. An example of why this may be the case is a recent study that engaged in experience sampling methodologies (ESM) (Killingsworth, 2021), which aggregated the resulting data (over one million real-time reports of emotional experiences) into a single value per user; effectively reducing the richness of the data collected. While this might have been done out of necessity with the purpose of comparing the new 2021 study's findings to a specific and highly publicised previous study (with reference to Kahneman & Deaton, 2010), it is nonetheless an example of some of the long-known challenges associated to novel methodologies such as ESM. Both the study design and the data analysis procedures more commonly found in literature have not always been conducted in such a way that enables looking into whether the temporal variability of the emotional experiences translates into different outcomes (Beal & Weiss, 2003).

This is a key gap in the literature as it hinders researchers understanding of how different affective experiences might be represented by characteristics such as personality traits (Burns & Ma, 2015). There have been many examples of ESM studies. As a result, a key novel aspect and aim of the present study was to use an advanced methodology (ESM) to analyse participant responses in its naturalistic form, as longitudinal panel data, to confirm whether time stable variables are suitable predictors of time varying variables. The main theoretical contribution of such a study is to extend the existing knowledge regarding the effect of personality on time varying emotional experiences, adding to the literature in the field of the science of happiness by confirming whether time stable and highly reliable variables (such as personality) may be used to predict affective experience – a time varying variable that is highly malleable. Given the aims of this study, it focused exclusively on the affective component of SWB – positive and negative affect (measured with SPANE, Diener, Wirtz, et al., 2010) –, and life satisfaction was not investigated, since the former is a time varying component of SWB, but the latter is stable and therefore has been widely researched before. This study investigated three hypotheses intended to extend the existing literature on the topic of SWB.

It has been suggested by past research that although the effect sizes were small, a significant gender difference was seen on various happiness inducing behaviours. For example, women scored higher for behaviours such as optimism, gratitude, and maintaining relationships, whereas men presented higher scores for behaviours like avoiding worrying and maintaining a status of flow (Warner & Vroman, 2011). Since these behaviours are believed to potentially be more common in one or the other gender, these differences should be reflected, to a degree, on momentary affective experiences. Given the large proportion of time that adults spend in the workplace, a secondary part of the first hypotheses is to extend the investigation to work-related individual characteristics of the participants, as these may be seen across genders, ages, and education levels. These are indicators that have been cited as being linked to happiness levels, albeit in studies with different methodologies or analysis strategies (for an example see Kahneman & Deaton, 2010; or Killingsworth, 2021).

H1a: Individual differences related to person-focused demographic characteristics age, gender, and education levels will explain differences in perceived momentary affect (positive and negative)

H1b: Specific work and career related demographic and individual differences such as years of experience, position in the company, type of employment, and income will explain differences in perceived affect (positive and negative)

Finally, we will look to add support to the body of evidence that personality traits are important predictors of SWB in two ways: firstly, by implementing multilevel modelling analysis to ESM longitudinal data, whereby it is expected that the data will support the notion that participants' personality will impact their perceived affective and emotional experiences, in real time. Secondly, by using both broad personality traits such as those measured by the Big Five model (Goldberg, 1992) and narrow personality traits measured by META (measure of entrepreneurial talents and abilities, Ahmetoglu et al., 2011) which focus on narrow traits such as the ability to identify opportunities, being innovative, self-confident, or having a proactive personality style (Leutner et al., 2014), which have been shown to be consistent indicators and predictors of entrepreneurial (and intrapreneurial) tendencies and success. As mentioned above, given the frequency with which adults are engaged in professional commitments, the inclusion of narrow personality traits is worthwhile investigating alongside broad ones.

H2: Personality traits will explain differences in perceived affect (positive and negative)

### *4.2 Results*

The data was cleaned and analysed with Stata/MP 17.0. The sample is composed of N=192 participants with five or more observations which resulted in a total of 6,397 observations, since this study uses a naturalistic approach to data collection via experience sampling at random times of the day. To ensure data robustness, two pre-emptive steps were taken: a) incomplete datasets were removed from the analysis, b) participants with fewer than five observations after removal of incomplete observations were removed from the analysis. The intention of these steps was to ensure that each individual's data represented a minimum of approximately one work week of their lives. The final sample used for analysis consisted of 6,227 observations, with two female participants who were found to have only three complete datasets each, which were excluded from the analysis. The final analysis sample (N=190) is divided into $N_{female}$ = 115, $N_{male}$ = 74, and $N_{other}$ = 1. Ages ranged from 18 to 75 years old ($M_{age}$ = 33.81, $SD_{age}$ = 8.53) with females, on average, being younger than males ($M_{f\_age}$ = 32.40, $SD_{f\_age}$ = 8.18; $M_{m\_age}$ = 36.27, $SD_{m\_age}$ = 8.58). The participants' length of participation ranged from 5 observations to 266 observations ($M_{length}$ = 37.85, $SD_{length}$ = 42.53). The large standard deviation value is expected and explained by the naturalistic data collection mechanism, which allowed participants to participate for as little or as long as they wished. To further verify whether an adequate number of participants remained past the average length mark, it was verified that fifty-seven participants (30%) response count was above average (i.e., over 38 observations), and 17 individuals' (8.95%) participation rate was equivalent to one standard deviation above average or higher (i.e., over 80 observations).

Female participants, on average, scored higher on both positive and negative affect scores, but the overall mean affect balance score was higher for males. For positive affect scores (PA), females scored higher on average with $M_{F\_PA}$= 22.52, $SD_{F\_PA}$= 5.70 (compared to $M_{M\_PA}$= 22.34, $SD_{M\_PA}$= 5.24), and the same trend was true for negative affect (NA) with $M_{F\_NA}$= 8.78, $SD_{F\_NA}$= 3.88 (compared to $M_{M\_NA}$= 8.49, $SD_{M\_NA}$= 3.98). The affect balance score (B) calculated from the difference between the two types of affect, such as "PA – NA" showed similar values with $M_{F\_B}$= 13.74, $SD_{F\_B}$= 8.31 (compared to $M_{M\_B}$= 13.85, $SD_{M\_B}$= 8.13). A closer look at each of the twelve affect experiences measured by SPANE (six positive, and six negative, see table 2 below), demonstrates that female participants scored higher on three positive emotions (content, good, positive) and lower on the remaining three (happy, joyful, pleasant), and they scored higher than males on five of the six negative emotions (angry, afraid, bad, negative, unpleasant) where the sixth emotion (sad) showed equal mean scores for both female and male participants. Females also scored higher, on average on the additional seventh negative scale (tired).

Reliabilities were calculated for SPANE, which had previously been demonstrated to have strong psychometric characteristics (e.g., Rahm, Heise & Schuldt, 2017), with an overall α = .88 for the subscale of positive affect (SPANE-PA), and α = .82 for negative affect (SPANE-NA). Data from this study showed very high reliability scores, with SPANA-Balance α = .93, SPANE-PA α = .74, and SPANE-NA α = .89.

**Table 2**

*Gender differences for affect scores and affect scale items.*

| **SPANE** | | **Female** | **Male** |
|---|---|---|---|
| **Affect Balance score** | Mean | 13.74 | **13.85** |
| | SD | 8.31 | 8.13 |
| **Positive Affect score** | Mean | **22.52** | 22.34 |
| | SD | 5.70 | 5.24 |
| **Negative Affect score** | Mean | **8.78** | 8.49 |
| | SD | 3.88 | 3.98 |
| **Content** | Mean | **3.62** | 3.53 |
| | SD | 1.16 | 1.09 |
| **Good** | Mean | **3.96** | 3.92 |
| | SD | 0.93 | 0.88 |
| **Happy** | Mean | 3.76 | **3.77** |
| | SD | 1.09 | 0.97 |
| **Joyful** | Mean | 3.53 | **3.54** |
| | SD | 1.19 | 1.04 |
| **Pleasant** | Mean | 3.73 | **3.78** |
| | SD | 1.08 | 0.96 |
| **Positive** | Mean | **3.97** | 3.95 |
| | SD | 0.89 | 0.89 |
| **Angry** | Mean | **1.31** | 1.26 |
| | SD | 0.69 | 0.64 |
| **Afraid** | Mean | **1.63** | 1.59 |
| | SD | 0.97 | 1.04 |
| **Bad** | Mean | **1.44** | 1.42 |
| | SD | 0.76 | 0.79 |
| **Negative** | Mean | **1.51** | 1.48 |
| | SD | 0.80 | 0.83 |
| **Sad** | Mean | 1.40 | 1.40 |
| | SD | 0.75 | 0.82 |
| **Unpleasant** | Mean | **1.51** | 1.40 |
| | SD | 0.83 | 0.79 |
| **Tired** | Mean | **2.79** | 2.33 |
| | SD | 1.27 | 1.26 |

*Note: The items emphasised in bold represent the highest of both scores between the genders.*

Table 3 below shows the descriptive statistics for the affective scores (positive, negative, and affect balance) with regards to the demographic variables that portray personal characteristics of the participants in this study that are not directly related to their current professional occupation: gender, age groups, and education level. The descriptive statistics show that females score higher both for positive ($M_{F\_PA}$ = 22.52, $SD_{F\_PA}$ = 5.70; $M_{M\_PA}$ = 22.34, $SD_{M\_PA}$ = 5.24) and negative affect ($M_{F\_NA}$ = 8.78, $SD_{F\_NA}$ = 3.88; $M_{M\_NA}$ = 8.49, $SD_{M\_NA}$ = 3.98), but lower for affect balance ($M_{F\_BA}$ = 13.74, $SD_{F\_BA}$ = 8.31; $M_{M\_BA}$ = 13.85, $SD_{M\_BA}$ = 8.13).

**Table 3**

*Descriptive statistics per time invariant demographic characteristic.*

| | | Stats | Positive Affect | | Negative Affect | | Affect Balance | |
|---|---|---|---|---|---|---|---|---|
| | | | Female | Male | Female | Male | Female | Male |
| Age group | Under 25 | $N_{obs}$ | 863 | 227 | 863 | 227 | 863 | 227 |
| | | Mean | 20.89 | 21.91 | 9.23 | 9.39 | 11.66 | 12.52 |
| | | SD | 5.97 | 6.56 | 4.20 | 4.58 | 8.85 | 9.55 |
| | 25-34 | $N_{obs}$ | 1383 | 564 | 1383 | 564 | 1,383 | 564 |
| | | Mean | 22.30 | 21.17 | 8.92 | 9.75 | 13.39 | 11.42 |
| | | SD | 5.17 | 5.27 | 3.80 | 4.21 | 8.01 | 8.54 |
| | 35-44 | $N_{obs}$ | 1343 | 1048 | 1343 | 1048 | 1,343 | 1,048 |
| | | Mean | 24.81 | 22.43 | 8.33 | 7.92 | 16.48 | 14.51 |
| | | SD | 5.00 | 4.93 | 3.48 | 3.70 | 7.36 | 7.47 |
| | 45-55 | $N_{obs}$ | 359 | 417 | 359 | 417 | 359 | 417 |
| | | Mean | 18.67 | 23.80 | 8.86 | 7.77 | 9.81 | 16.03 |
| | | SD | 5.89 | 4.76 | 4.58 | 3.54 | 8.23 | 7.49 |
| | Over 55 | $N_{obs}$ | - | 15 | - | 15 | - | 15 |
| | | Mean | - | 26 | - | 7.4 | - | 18.6 |
| | | SD | - | 2.88 | - | 1.72 | - | 3.96 |
| Education level | A-levels | $N_{obs}$ | 436 | 331 | 436 | 331 | 436 | 331 |
| | | Mean | 20.38 | 19.41 | 9.34 | 9.73 | 11.04 | 9.69 |
| | | SD | 5.95 | 4.80 | 4.35 | 5.08 | 9.15 | 8.96 |
| | Bachelor's degree | $N_{obs}$ | 1026 | 949 | 1026 | 949 | 1,026 | 949 |
| | | Mean | 22.53 | 22.20 | 8.41 | 8.43 | 14.12 | 13.77 |
| | | SD | 6.44 | 5.13 | 3.70 | 3.87 | 8.69 | 7.71 |
| | Master's degree | $N_{obs}$ | 2324 | 991 | 2324 | 991 | 2,324 | 991 |
| | | Mean | 22.98 | 23.45 | 8.79 | 8.14 | 14.19 | 15.32 |
| | | SD | 5.28 | 5.09 | 3.84 | 3.56 | 7.89 | 7.75 |
| | Doctoral degree | $N_{obs}$ | 162 | - | 162 | - | 162 | - |
| | | Mean | 21.62 | - | 9.51 | - | 12.11 | - |
| | | SD | 4.38 | - | 3.90 | - | 7.80 | - |
| Total | | $N_{obs}$ | 3948 | 2271 | 3948 | 2271 | 3,948 | 2,271 |
| | | Mean | 22.52 | 22.34 | 8.78 | 8.49 | 13.74 | 13.85 |
| | | SD | 5.70 | 5.24 | 3.88 | 3.98 | 8.31 | 8.13 |

The group that shows the highest average positive affect score is the over 55 years old males (*M* = 26.00, *SD* = 2.88), although it is important to note that this is a particularly small group, since only two participants are included (15 observations). The immediately subsequent highest average positive affect score is reported for 35-44 years old females (N=27 with 1,343 observations, *M* = 24.81, *SD* = 5.00), followed by males with master's degrees (N=32 with 991 observations, *M* = 23.45, *SD* = 5.09). Females in the age group 45-55 years old reports the lowest average positive affect (N=12 with 359 observations, *M* = 18.67, *SD* = 5.89). As for the group with the highest reported average negative affect, the males in the age group 25-34 show the highest value (N=20 with 564 observations, *M* = 9.75, *SD* = 4.21) followed by males whose highest educational qualification is A-Level (N=12 with 331 observations, *M* = 9.73, *SD* = 5.08). In turn, the group with the lowest reported average of negative affect once again refers to the small group (N=2) of male participants over 55 years old (*M* = 7.40, *SD* = 1.72), followed by the group of males in the age group 45 to 55 years old (N=10 with 417 observations, *M* = 7.77, *SD* = 3.54) and males between 35 and 44 years old (N=29 with 1048 observations, *M* = 7.92, *SD* = 3.70).

Participants were also grouped with regards to demographic information that pertains to their current professional occupation. Table 4 below contains the descriptive statistics for positive, negative, and affect balance where participants are grouped by years of experience, position level within the company (entry, mid, or senior level, management, or non-management role), type of employment (full-time, part-time, or self-employed), and income.

**Table 4**

Descriptive statistics based on employment characteristics demographics.

| | | | Positive Affect | Negative Affect | Affect Balance |
|---|---|---|---|---|---|
| Years of experience | Less than 1 year | N | 756 | 756 | 756 |
| | | Mean | 22.37 | 8.92 | 13.44 |
| | | SD | 5.54 | 3.75 | 8.12 |
| | 1 to 3 years | N | 1027 | 1027 | 1027 |
| | | Mean | 21.24 | 9.67 | 11.57 |
| | | SD | 5.59 | 4.27 | 8.84 |
| | 3 to 5 years | N | 625 | 625 | 625 |
| | | Mean | 21.42 | 9.06 | 12.37 |
| | | SD | 4.69 | 3.74 | 7.26 |
| | 5 to 10 years | N | 1125 | 1125 | 1,125 |
| | | Mean | 23.93 | 8.16 | 15.77 |
| | | SD | 5.03 | 3.30 | 7.22 |
| | Over 10 years | N | 1932 | 1932 | 1932 |
| | | Mean | 22.93 | 7.80 | 15.14 |
| | | SD | 5.69 | 3.47 | 7.83 |
| | N/A | N | 284 | 284 | 284 |
| | | Mean | 22.43 | 8.53 | 13.90 |
| | | SD | 6.14 | 3.76 | 8.58 |
| | Total | N | 5749 | 5749 | 5,749 |
| | | Mean | 22.56 | 8.52 | 14.04 |
| | | SD | 5.53 | 3.74 | 8.07 |
| Position in the company | Entry level | N | 530 | 530 | 530 |
| | | Mean | 20.95 | 9.02 | 11.92 |
| | | SD | 6.42 | 4.12 | 8.92 |
| | Mid-level | N | 1705 | 1705 | 1705 |
| | | Mean | 22.68 | 9.02 | 13.66 |
| | | SD | 5.07 | 3.79 | 7.95 |
| | Mid manager | N | 769 | 769 | 769 |
| | | Mean | 23.38 | 7.94 | 15.44 |
| | | SD | 5.85 | 3.44 | 7.84 |
| | Senior level | N | 1060 | 1060 | 1060 |
| | | Mean | 22.46 | 8.57 | 13.89 |
| | | SD | 4.80 | 3.62 | 7.07 |
| | Senior manager | N | 1245 | 1245 | 1245 |
| | | Mean | 22.90 | 8.21 | 14.69 |
| | | SD | 5.93 | 4.21 | 8.97 |
| | N/A | N | 883 | 883 | 883 |
| | | Mean | 21.49 | 9.15 | 12.34 |
| | | SD | 5.56 | 4.16 | 8.54 |
| | Total | N | 6192 | 6192 | 6192 |

| | | | Positive Affect | Negative Affect | Affect Balance |
|---|---|---|---|---|---|
| | | Mean | 22.46 | 8.67 | 13.79 |
| | | SD | 5.55 | 3.92 | 8.25 |
| **Type of employment** | **Full time** | N | 4016 | 4016 | 4,016 |
| | | Mean | 22.91 | 8.26 | 14.64 |
| | | SD | 5.28 | 3.70 | 7.79 |
| | **Part time** | N | 1474 | 1474 | 1,474 |
| | | Mean | 22.07 | 9.19 | 12.88 |
| | | SD | 5.77 | 3.93 | 8.48 |
| | **Self employed** | N | 737 | 737 | 737 |
| | | Mean | 20.81 | 9.86 | 10.95 |
| | | SD | 6.04 | 4.60 | 9.26 |
| | **Total** | N | 6227 | 6227 | 6,227 |
| | | Mean | 22.46 | 8.67 | 13.79 |
| | | SD | 5.54 | 3.92 | 8.25 |
| **Income** | **Under £15,599** | N | 1477 | 1477 | 1,477 |
| | | Mean | 23.30 | 8.26 | 15.03 |
| | | SD | 5.37 | 3.29 | 7.53 |
| | **£15,600 to £25,999** | N | 816 | 816 | 816 |
| | | Mean | 20.53 | 9.17 | 11.36 |
| | | SD | 5.49 | 3.99 | 8.33 |
| | **£26,000 to £36,399** | N | 649 | 649 | 649 |
| | | Mean | 22.37 | 9.10 | 13.27 |
| | | SD | 5.72 | 4.02 | 8.37 |
| | **£36,400 to £51,999** | N | 480 | 480 | 480 |
| | | Mean | 21.24 | 9.79 | 11.45 |
| | | SD | 4.26 | 4.27 | 7.43 |
| | **Over £52,000** | N | 1435 | 1435 | 1435 |
| | | Mean | 22.59 | 8.22 | 14.37 |
| | | SD | 5.23 | 3.88 | 7.86 |
| | **N/A** | N | 1276 | 1276 | 1276 |
| | | Mean | 23.10 | 8.55 | 14.55 |
| | | SD | 6.06 | 4.06 | 8.91 |
| | **Total** | N | 6133 | 6133 | 6,133 |
| | | Mean | 22.46 | 8.64 | 13.82 |
| | | SD | 5.54 | 3.88 | 8.21 |

The group that showed the highest level of positive affect, on average, was the group of participants whose professional experience ranged from five to ten years (N=18 with 1,125 observations, *M* = 23.93, *SD* = 5.03), followed by those who old mid-management positions in their current employment (N=22 with 769 observations, *M* = 23.38, *SD* = 5.85). On the other hand, the lowest positive affect, on average, was reported by the group of people whose yearly income falls in the bracket £15,600 to £25,999 (N=18 with 816 observations, *M* = 20.53, *SD* = 5.49), followed by self-employed participants (N=20 with 737 observations, *M* = 20.81, *SD* = 5.77) which was also the group with the highest negative affect, on (*M* = 9.86, *SD* = 4.60). The lowest average negative affect was reported by participants with over ten years of professional experience (N=43 with 1,932 observations, *M* = 20.81, *SD* = 5.77), followed by those with mid-management positions (*M* = 7.94, *SD* = 3.44) who were also reported as one of the highest average positive affect scores, as mentioned above (N=22; 769 observations). It is worth of note the fact that the amongst the higher positive and lower negative affect scores, resulting in the highest affect balance score are the most experienced participants (ten years or more) (*M* = 15.14, *SD* = 7.83), and amongst the lowest positive and highest negative affect, resulting in a low affect balance score are those participants who are self-employed (*M* = 10.95, *SD* = 9.26).

Table 5 summarises the participants' personality traits measured by the BFI-10 (Rammstedt & John, 2007) and META (Ahmetoglu et al., 2011). The first instrument focuses on broad personality traits such as agreeableness or extraversion as identified in the Big Five Model (Goldberg, 1992), whereas the latter describes the participants' personality with regards to entrepreneurial talents and abilities, which are related to workplace innovation and disruption (Leutner et al., 2014).

The BFI-10 was selected due to its conveniently reduced item pool allowing participants to respond quickly – a valuable gain for a longitudinal study that collects data via experience sampling –, whilst reporting to retain good reliability in previous literature (α = .75, Rammstedt & John, 2007). During this study, Cronbach's alpha was calculated and it showed acceptable reliability (α = .56) although it was a less encouraging value than previously reported. Since the scale is very compressed, it would require rather large correlations between each pair of items to result in very high reliability scores. In this case, each subscale was comprised of two items, and the reliability of each subscale was weak, particularly for agreeableness and openness.

(extraversion α = .64; agreeableness α = .17; conscientiousness α = .46; neuroticism α = .40; openness α = .13). The reliability of the META was also calculated evidencing very high reliability overall (α = .83). Each subscale contained four items and the subscale reliabilities was good in all but one of the scales – vision (α = .42) – where it was acceptable but low. The remaining subscales were opportunism (α = .75), creativity (α = .60), and proactivity (α = .61).

**Table 5**

*Descriptive statistics for the BFI-10 and META instruments.*

| | Stats | $N_{obs}$ | Mean | SD |
|---|---|---|---|---|
| BFI-10 | Openness | 6,134 | 6.91 | 1.53 |
| | Neuroticism | 6,134 | 5.64 | 1.68 |
| | Extraversion | 6,134 | 6.60 | 2.05 |
| | Conscientiousness | 6,134 | 7.33 | 1.75 |
| | Agreeableness | 6,134 | 7.50 | 1.52 |
| META | Opportunism | 6,002 | 14.98 | 3.50 |
| | Creativity | 6,002 | 17.95 | 2.88 |
| | Vision | 6,002 | 19.35 | 2.64 |
| | Proactivity | 6,002 | 16.25 | 3.04 |

This summary shows that the broad personality traits that scored higher, on average, were agreeableness (*M* = 7.50, *SD* = 1.52) and conscientiousness (*M* = 7.33, *SD* = 1.75), with neuroticism's average score being the lowest (*M* = 5.64, *SD* = 1.68). The entrepreneurial talents and abilities measure shows the highest average reported as the score for vision (*M* = 19.35, *SD* = 2.64), and the lowest average score was on the opportunism dimension (*M* = 14.98, *SD* = 3.5). These results suggest that the sample analysed was made up of participants who are considerate and thoughtful, given the higher scores on a combination of less risk-prone traits in the BFI-10 alongside the lower scores on the META for the dimensions that may have indicated more risk-prone individuals (such as opportunism and proactivity).

There are different statistical procedures and tests that inherently address the issues posed by panel data, including the fact that there is no independence of the standard error terms or that the dataset may be unbalanced, as is the case with the present study. Given the type of panel data being studied and the aim of this research, multilevel longitudinal modelling of continuous outcomes suggests that if the independent variables being studied do not vary over time, then the use of a random effects (RE) model is appropriate to estimate whether the independent variable(s) under analysis are suitable estimators of the dependent variable. By design, Fixed Effects (FE) models work in such a way that all time-invariant differences between individuals are controlled for, and therefore cannot be used to investigate whether there are time-invariant causes for the variance of the dependent variable(s) (Kohler & Kreuter, 2005). Since this study focuses on variables that have little to no variation overtime (such as demographic variables and personality), all upcoming models used for estimation purposes will be random effects (RE) models.

### *4.2.1 Momentary positive affect predicted by personal demographics*

The categorical nature of the variables that represent demographic individual differences is defined by the participant either being included or excluded from each level of the categorical variable (e.g., a participant who has a master's degree, is only represented in this group, but not in the remaining levels of the "education" variable). For each multilevel RE model, one category level is considered as the basis for the analysis, i.e., the model presumes that this base category level is zero (not present; controlled for), while estimating the effect of the remaining variables. To determine whether there is support for the hypothesis that individual differences measured by commonly used demographic variables (age, gender, education level) has an impact on longitudinal experiences of affect, the first step was to determine whether each individual independent variable is a statistically significant predictor of longitudinal positive affect, and depending on which of the variables were found to be relevant, another model would be fitted to the data to investigate how a combination of relevant factors helps understand positive affect experienced by the participants. Individual RE models were conducted with the dependent variable positive affect, and each of the demographic variables age, gender, and education as independent variables. Results showed that age and education as individual differences demographic variables were statistically significant predictors of positive affect scores ($z$ = 2.56, $p$ = .01 and $z$ = 2.05, $p$ = .04), but gender was not a significant predictor of positive affect ($z$ = -0.18, $p$ = .86). Further, models were fitted to investigate how each of the categorical variable levels related to positive affect. Compared to the age group "under 25", a participant's positive affect score is likely to be 1.89 points higher if they are 25 to 34 years old ($z$ = 2.64, $p$ = .008) or 2.78 points higher if they are 35 to 44 years old ($z$ = 3.82, $p$ < .001). Having a master's degree is likely to significantly increase positive affect by 1.96 points ($z$ = 2.48, $p$ = .013), with the other levels revealing no significant results, compared to those with "A-levels". Individually, these models predicted that the significant levels of age and education helped explain 39.96% and 41.45%, respectively, of the variation in positive affect. This is also referred to as ICC (intraclass correlation), whereby it is interpreted that in a model where age is used as the only predictor of the positive affect score (which varies a) between individuals, b) within individuals, over time), the variations seen in the data were explained up to 39.96% by the age of the individual. Or, to put it differently, whichever characteristics participants share at each age group, these similarities help explain a portion of the variance seen (in this case, up to nearly 40%).

Finally, a model was fitted to include both the age and educational attainment categorical levels as predictors of positive affect. The results showed that in this joint model, education levels were not significant, and the only age group that significantly predicted the dependent variable was that of individuals aged 35 to 44 ($z$ = 3.03, $p$ = .002), with both the age groups of 25 to 34 and over 55 years old approaching significance ($z$ = 1.95, $p$ = .052 and $z$ = 1.93, $p$ = .054; respectively). These findings seem to suggest that the underlying unmeasurable factors associated with the educational level that might explain some of the differences in positive affect, when looked at in isolation, are in fact, related to the age (or possibly life stage) of the participants, which then translated to a joint model whereby controlling age alongside education, the latter no longer significantly explained differences in the dependent variable. This model was estimated to explain 40.18% of the differences found.

*4.2.2 Momentary negative affect predicted by personal demographics*

Individual RE models were fitted to the data with the dependent variable negative affect, and each of the independent variables age, gender, and education as independent variables. The results showed an opposite scenario to that of positive effect. Age and education were not statistically significant predictors of negative affect scores ($z$ = -1.06, $p$ = .289 and $z$ = -0.09, $p$ = .93; respectively), but gender differences indicate that if a participant is male, their negative affect score is 0.99 points lower than that of a female participant ($z$ = -2.14, $p$ = .032) and this model was estimated to explain 49.19% of the negative affect variation. Since only one of the three variables is a significant predictor of negative affect, it became immaterial to fit additional models that were not supported by the data analysis.

*4.2.3 Momentary affect balance predicted by personal demographics*

When analysing the effect of individual differences measured by demographic data on affect balance, the initial models were fitted to individually investigate which of the three independent variables are significant predictors of the affect balance score. These models showed that age is a significant predictor ($z$ = 2.19, $p$ = .029), but education and gender were not ($z$ = 1.34, $p$ = .180 and $z$ = 0.99, $p$ = .322; respectively).

To investigate how each of the age groups related to affect balance, a new model was fit to the data where the age groups' impact on affect balance were analysed categorically. The age group reported to have the highest improvement on affect balance scores (compared to the age group "under 25") includes the participants whose age varied between 35 and 44 years old, whose score were 4.22 points higher than other age groups ($z = 3.68$, $p < .001$), followed by the participants with ages between 25 and 34 whose score improved by 2.81 points ($z = 2.5$, $p = .013$). For individuals aged 45 to 54 and those over 55 years old there were no significant affect balance score differences ($z = 0.63$, $p = .529$ and $z = 1.76$, $p = .078$; respectively). This model explained 42.13% of the affect balance score differences.

The H1a hypothesis that individual differences measured by personal demographic variables contribute to explain momentary affect variance was partially supported by these results. Age was shown to be a significant predictor of positive and affect balance scores, education had a significant effect on positive affect scores, while gender was only useful in estimating negative affect differences.

#### *4.2.4 Momentary positive affect predicted by work and career demographics*

To determine whether there is support for the H1b hypothesis that demographic variables commonly used as professional indicators (years of experience, position in the company, employment type, income) have an impact on longitudinal experiences of affect, the first step was to determine whether each individual independent variable is a statistically significant predictor of longitudinal positive affect using RE models. Upon analysis, the two professional demographic variables shown to be significant predictors of momentary positive affect were employment type (i.e., whether the individual works full-time, part-time, or is self-employed) and position held in the company. With regards to employment type, the analysis revealed that being self-employed negatively impacts positive affect by 1.79 points ($z = -2.49$, $p = .013$), and an estimated 41.07% of variation in positive affect being due to this variable. The position held in the company was represented by six categories: entry level positions, mid-level non-managerial roles, mid-management roles, senior but non-managerial roles, senior managers, and “prefer not to answer” or blank observations. Since it would not be logical to analyse results for the sixth category (i.e., observations without meaningful data), the category of "entry level" was used as the basis instead (i.e., incorporated in the model as zero – i.e., what happens to the positive affect score if the participants did not belong to this group). Holding a mid-level but not managerial position significant and positively impacts positive affect by improving the score by 3.11 points ($z$ = 2.84, $p$ = .004), a mid-management positions improves the score of positive affect by 4.65 points ($z$ = 3.90, $p$ < .001), a senior but not managerial position increases the positive affect score by 3.74 points ($z$ = 3.35, $p$ = .001) and holding a senior management position increases the score by 3.67 points ($z$ = 3.44, $p$ = .001). This model estimates that this variable's differences explain 40.45% of positive affect variance.

A dual model was fitted to examine how a combination of employment type and position held impact positive affect experienced by the participants. The results show that in the joint model the level of the position held remains a significant predictor of positive affect (mid-level but not managerial coeff. = 2.89 points, $z$ = 2.65, $p$ = .008; mid-management coeff. = 4.32 points, $z$ = 3.60, $p$ < .001, senior but not managerial coeff. = 3.74 points, $z$ = 3.50, $p$ = .002; senior management coeff. = 3.38 points, $z$ = 3.15, $p$ = .002), however, being an entrepreneur no longer significantly predicts changes in PA (coeff. -1.78, $z$ = -1.69, $p$ = .92). This suggests that by adding complexity to the model, we learn that the negative effect of being new to one's job and career takes an even larger toll on the participant's positive effect, all else being equal. This model explained 40.11% variation in positive affect scores.

### *4.2.5 Momentary negative affect predicted by work and career demographics*

To determine whether professional indicators (years of experience, position in the company, employment type, income) have an impact on longitudinal experiences of affect, models were computed to analyse the extent to which each independent variable is a statistically significant predictor of longitudinal negative affect. Upon analysis, there was one independent variable with a significant impact on negative affect: employment type. The results show that being self-employed further increases negative affect scores by 1.41 points (*z* = 2.39, *p* = .017), whereas holding a part-time position does not significantly affect negative emotions (*z* = 0.39, *p* = .695). This model explained 49.27% of the variance in negative affect.

#### *4.2.6 Momentary affect balance predicted by work and career demographics*

The same professional demographics (years of experience, position in the company, employment type, income) were analysed to identify whether they have an impact on longitudinal experiences of affect. The two variables who significantly affect the balance scores were experience, which increases affect balance by 0.61 points (*z* = 2.08, *p* = .037) and employment type, which reduces the score by 1.35 points (*z* = -2.48, *p* = .013). Position in the company and income are not significant predictors of affect balance (*z* = 0.65, *p* = .518 and *z* = 0.74, *p* = .458; respectively). As a result, a combined model that simultaneously uses experience and employment type as independent variables was computed. The results showed that when combined, both variables continue to be significant predictors of the affect balance score, with experience having a positive impact (increasing the score by 0.69 points) and employment having a negative impact (decreasing the score by -1.68 points) (*z* = 2.39, *p* = .017 and *z* = -2.79, *p* = .005; respectively). This model explained 39.39% of the balance scores variance.

The hypothesis that professional demographic variables and indicators helps explain momentary affect variance was partially supported by these results, with being an entrepreneur (employment type) shown to be a significant negative predictor of positive and affect balance scores, while increasing the negative affect score; holding a mid-management position in a company significantly increases positive affect; and experience levels positively impact the affect balance score. Income, arguably one of the most common indicators, was shown to not have a significant impact on any of the momentary and longitudinal affect experience scores.

A model was computed to integrate all demographic variables to determine its suitability to estimate variations in momentary affective experiences. As a result, a model with all the demographic variables being studied – age, gender, education, experience, position in the company, employment type, and income, showed that none of the variables are significant predictors of positive affect or affect balance, with negative affect being significantly predicted only by being self-employed (coeff. = 2.36, $z = 2.15$, $p = .031$). Since some of the initial variables had been shown not to be good individual predictors of affective experience, a model was computed where only those variables that had shown a significant impact were retained. In this model, the combined effect of age, educational level, and position within the company were calculated with a RE model to predict positive affect. The results showed that when combined, age and education are not significant predictors, with holding an entry level position being the only significant (and negative) predictor of positive affect, with the ability to decrease the positive affect score by 2.37 points ($z = -2.17$, $p = .03$). An estimated 39.86% of positive affect variance is explained by this combined model. A negative affect regression model was calculated using the original variables that were significant when analysed in isolation: gender and employment type. The results show that males experiences of negative affect are significantly lower, by 0.98 points ($z = -2.02$, $p = .043$), and being self-employed significantly increases the negative affect scores by 1.22 points ($z = 2.05$, $p = .04$). This model estimated that 48.75% of the negative affect variance could be explained. With regards to affect balance scores, age and experience were combined into a RE model, which revealed that together neither variable was a significant predictor of the affective experience. A combined model featuring every demographic variable also revealed no significant predictors.

#### *4.2.7 Real-time momentary positive affect predicted by personality*

To investigate the H2 hypothesis of whether personality measures are significant predictors of momentary positive affect, two personality models were used:

one that focuses on broad personality traits, and one which measures narrower personality traits. Participants' personality was measured based on the popular Five Factor Model (also referred to as the "Big Five Model") (Goldberg, 1992), and based on the META which focuses on narrow personality characteristics related to entrepreneurial talents and abilities (i.e., innovation, disruption, etc.) (Ahmetoglu et al., 2011).

A model was fitted for each individual personality trait first. In these mono-trait models, results found that four out of the five traits were significant predictors, although the estimated score change was small; agreeableness, extraversion, conscientiousness, and neuroticism were significant predictors whereas openness to experiences was not. Agreeableness increased positive affect by 0.40 points ($z$ = 2.08, $p$ = .037), extraversion by 0.44 points ($z$ = 3.3, $p$ = .001), conscientiousness by 0.74 points ($z$ = 5.01, $p$ < .001), and neuroticism reduced the positive affect score by 0.43 points ($z$ = -2.71, $p$ = .007). Openness did not have a significant impact on positive affect ($z$ = 1.11, $p$ = .267). Since these variables are part of a well-established theoretical framework, a model was computed which included all five traits, including openness. When analysed together, the results indicated that personality traits are not an especially strong predictor of positive affect, with only conscientiousness being a significant predictor, increasing the score by 0.61 points ($z$ = 3.91, $p$ < .001). Agreeableness ($z$ = 0.97, $p$ = .334), extraversion ($z$ = 1.33, $p$ = .183), neuroticism ($z$ = -1.77, $p$ = .076), and openness ($z$ = 0.85, $p$ = .396) were not relevant predictors of momentary positive affect experiences. This model estimated that the variance of positive affect explained by these broad personality traits was 38%.

To investigate whether narrower personality traits, as measured by META, were good predictors of positive affect scores, a similar sequence of steps was taken: firstly, individual models were created to determine whether, on their own, the personality traits were likely to predict changes in the affect score, followed by a complete model which included all four traits measured by META: opportunism, creativity, vision, and proactivity. The first set of single trait models showed that all four traits were significant predictors albeit, as with the broad traits reported before, their impact on the scores was small. Opportunism was a positive and significant predictor which increases the score by 0.23 points ($z$ = 2.78, $p$ = .005), as was creativity that increased the score by 0.20 points ($z$ = 2.05, $p$ = .041), vision improved the positive affect score by 0.41 points ($z$ = 4.00, $p$ < .001), and proactivity raised the score by 0.23 points ($z$ = 2.46, $p$ = .014). When combined, the trait vision was the only significant predictor of positive affect, while controlling for the other traits – it added 0.33 points to the score ($z$ = 2.71, $p$ = .007). This model estimated that the variance of positive affect explained by these personality traits was 38.50%.

### *4.2.8 Momentary negative affect predicted by personality*

Similarly, the process described above was followed to investigate whether negative affect was sufficiently explained by broad and narrow personality traits. Negative affect was computed as the dependent variable in a series of RE regression models first with the five factor model personality traits and then the META traits. Models included, first, each trait individually computed as the independent variable, followed by a combined model with the five or four traits that make up the full model. With regards to the broad traits, the results show that conscientiousness was a significant and negative predictor which decreased the negative affect score by 0.46 points ($z$ = -3.84, $p$ < .001), while neuroticism was a positive and significant predictor, increasing the score by 0.27 points ($z$ = 2.17, $p$ = .003). As noted above regarding positive affect, these are relatively small alterations to the positive affect score overall. When analysing the combined effect of the complete set of traits in the five-factor personality model, conscientiousness becomes the only significant predictor of negative affect, reducing the score by 0.44 points ($z$ = 3.51, $p$ < .001). Agreeableness ($z$ = -0.99, $p$ = .322), extraversion ($z$ = 0.97, $p$ = .335), neuroticism ($z$ = 1.82, $p$ = .069), and openness ($z$ = -0.78, $p$ = 433) were not relevant predictors of momentary negative affect experiences.

As for META's narrower personality traits, the models showed that two traits were significant predictors of negative affect, with their impact on the negative affect scores being small as reported previously. Vision reduced the negative affect score by 0.30 points ($z$ = -3.32, $p$ < .001), while proactivity lowered the score by 0.19 points ($z$ = -2.36, $p$ = .018). Opportunism and creativity were not significant predictors ($z$ = -0.76, $p$ = .445 and $z$ = -1.28, $p$ = .202; respectively). When combined, the trait vision was the only significant predictor of negative affect, while controlling for the other traits – it lowers the negative affect score by 0.30 points ($z$ = -2.83, $p$ = .005). This model estimates that the variance of negative affect explained by these personality traits is 49.85%.

#### *4.2.9 Momentary affect balance predicted by personality*

A model was fitted for each personality trait as the independent variable to determine their individual predictor potential when it comes to affect balance scores. Agreeableness, extraversion, conscientiousness, and neuroticism were shown to be significant predictors whereas openness to experiences was not. Agreeableness increased positive affect by 0.68 points ($z$ = 2.36, $p$ = .018), extraversion by 0.53 points ($z$ = 2.54, $p$ = .011), conscientiousness by 1.19 points ($z$ = 5.35, $p$ < .001), and neuroticism reduced the affect balance score by 0.70 points ($z$ = -2.90, $p$ = .004). Openness did not have a significant impact on affect balance ($z$ = 1.03, $p$ = .301). When analysed together, the results show that conscientiousness significantly predicts the balance score, increasing it by 1.05 points ($z$ = 4.47, $p$ < .001) and neuroticism significantly reduces the score by 0.50 points ($z$ = -2.13, $p$ = .033). Agreeableness ($z$ = 1.16, $p$ = .244), extraversion ($z$ = 0.37, $p$ = .71), and openness ($z$ = 0.98, $p$ = .328) were not significant predictors of affect balance scores.

With regards to narrow META personality traits, opportunism was a positive and significant predictor which increases the affect balance score by 0.28 points ($z$ = 2.14, $p$ = .033), as was creativity which improves the score by 0.30 points ($z$ = 1.97, $p$ = .049), vision improved the affect balance score by 0.71 points ($z$ = 4.35, $p$ < .001), and proactivity raised the score by 0.42 points ($z$ = 2.82, $p$ = .005). When combined, vision was the only significant predictor of affect balance scores, while controlling for the other traits – it adds 0.62 points to the score ($z$ = 3.26, $p$ = .001). This model estimates that the variance of affect balance explained by these personality traits is 41.35%.

The hypothesis that individual differences measured by personality scores helps explain momentary affect variance was partially supported by these results. Neither of the two personality frameworks used in this study translated into a full set of variables capable of explaining the affective experience differences. For those variables that did predict some changes in the scores, they were generally small differences of less than 1 point difference (from a range of 6 to 30 points for positive and negative affect, and -24 to 24 for affect balance).

To finalise the analysis, a RE model was computed to calculate the regression coefficients for a model that includes the variables found to (individually) be significant predictors to investigate whether their combination would increase the ability to predict positive, negative, and affect balance scores. Some variables' effect on the dependent variable might overlap with one another (since the correlation between some of these variables has been established in past literature, such as income and personality, or age and experience), which could lead to the final model not necessarily bringing additional explanatory value of the momentary affective changes seen in the data. A model including broad and narrow personality traits determined that conscientiousness and vision remain the only two significant and positive predictors of positive affect (coeff. = 0.42, $z$ = 2.49, $p$ = .013 and coeff. = 0.25, $z$ = 2.16, $p$ = .031; respectively), negative predictors of negative affect which suggests a protective quality (coeff. = -0.35, $z$ = -2.43, $p$ = .015 and coeff. = -0.24, $z$ = -2.34, $p$ = .019; respectively), and positive predictors of affect balance (coeff. = 0.77, $z = 2.95$, $p = .003$ and coeff. = 0.49, $z = 2.69$, $p = .007$; respectively). The level of variance each model estimated to be explained by the independent variables was 36.35%, 47.34%, and 38.15% respectively.

A model including both demographic and personality independent variables was computed for each of the affective scores being investigated. When calculating the effect of age, education, position in the company, type of employment, broad and narrow personality traits, it was found that this model explains 34.75% of the variance in positive affect, age and education are not significant predictors when controlling for the remaining variables, the position in the company category of being at an entry level was the only position with a significant and negative impact on the affective experience (coeff. = -3.00, $z = -2.27$, $p = .023$), broad personality traits extraversion and conscientiousness have a significant and positive effect (coeff. = 0.30, $z = 1.97$, $p = .049$ and coeff. = 0.44, $z = 2.41$, $p = .016$, respectively), as well as narrow personality trait vision which also positively predicts positive affect (coeff. = 0.25, $z = 2.07$, $p = .038$). Overall, this model predicts 34.75% of the PA variance. A model with gender, employment type, broad and narrow personality traits was estimated to predict 46.36% of the negative affect variance. According to this model, it was determined that males experience significantly lower levels of negative affect than females, with scores 1.04 lower ($z = -2.01$, $p = .044$), and vision retaining its significance as a predictor of the negative affective experience, helping to reduce the overall score (coeff. = -0.27, $z = -2.63$, $p = .008$). The overall model to predict affect balance included the variables age, experience, broad and narrow personality traits. The model showed that only personality traits were significant predictors of the affect balance score; conscientiousness (coeff. = 0.61, $z = 1.99$, $p = .047$) and vision (coeff. = 0.52, $z = 2.53$, $p = .012$). The total balance variance explained was 35.91%.

### *4.3 Discussion*

This study's aims were to investigate whether time stable variables were adequate predictors of momentary, real-time, affective experiences as had been suggested by previous research. This was done by investigating the impact of demographic variables commonly used as indicators (age, gender, education, income, etc.) as well as broad and narrow personality traits, measured using the Big Five and META models, respectively. It was hypothesised, based on prior research that suggested that time stable variables were strong predictors of affective experiences, that both the demographic variables (hypotheses H1a and H1b) as well as personality traits (broad and narrow) (hypothesis H2) would be suitable predictors of momentary (real time) affect experiences.

Multilevel longitudinal random effects regression models were computed to determine the extent to which the independent variables were suitable estimators of positive affect, negative affect, and affect balance such that the fact that the dependent variable (i.e., the affect scores) is continuous and varies between and within subjects, as well as through time, was appropriately handled. Results showed that the individual demographic variables were inconsistently associated to affective experience, since some variables predicted positive affect (age and education), others predicted negative affect (employment type; being self-employed), and others affect balance (age and experience). The individual impact of these independent variables was mostly small, showing between a 0.61 and 4.22 points difference in the affective scores. Personality traits were also found to be significant predictors of affective experience, with their individual impact being more consistently seen across traits but their effects were smaller than what was seen for the demographics, with an impact of 0.19 to 1.19 points difference on the resulting affective scores. When more complex models that looked to combine multiple demographic variables and/or personality traits, the results indicated that few of the variables retained their relevance as predictors of affective experience. This is likely caused by the independent variables sharing unknown or unmeasurable variance. The RE regressions seem to indicate that the random effects might, in fact, include shared characteristics across variables, and therefore when computed together (allowing the model to control for these effects), fewer individual variables retain their ability to add information to the regression model, and when combined are no longer significant factors. For example, this could mean that a few demographic variables share some type of temporality commonality. It would seem reasonable to expect a convergence of individual demographic variables between participants in terms of their age, their educational attainment at a particular age, stage of their career, or between the position that they occupy in the company and their income. In other words, for example, it would be a reasonable expectation that early to mid-twenties individuals might have a larger proportion of undergraduate degrees than doctoral degrees, have a lower number of years of work experience, might have an entry level job, and lower income. In contrast, for participants over fifty, they may have more established careers, occupy hierarchically higher positions within their companies, and earn higher wages. This seems like a reasonable explanation as to why several variables became statistically non-significant once combined into a more comprehensive model, that simultaneously does not explain a higher percentage of variation in the dependent variable.

Similar reasoning could be applied to the personality scales and their aptitude to explain a portion of the variance in the dependent affective variables. Contrary to the demographic variables, all personality traits (broad and narrow) were shown to be individually significant predictors of affect. However, the affective scores differences seen as a result of a higher score in each personality trait were even smaller as mentioned above. For example, the smallest increment in a model using individual personality traits as predictors was the effect of proactivity on reducing experiences of negative affect by 0.19 points (for each 1-point increase in proactivity). Since the scale score ranges from six to thirty points, this corresponds to a mere 0.63% improvement over the negative affect score. Despite the overarching finding that all nine individual personality traits (five broad traits from the five-factor model, and four narrow traits from META) were significant predictors, this also dissipated when new models were computed to mimic the structure of each framework, with conscientiousness (BFI-10) and vision (META) becoming the only two consistent traits that were significant predictors of affective score changes. This finding is in line with what some authors believe to be a demonstration that more accurate ways to assess time varying components of SWB are necessary, acknowledging that individual dispositions have been pointed out as not being sufficiently dynamic to fully appreciate and encapsulate all that SWB entails (Friedman & Kern 2014; Sonnentag, 2015).

Enormous amounts of empirical data have been produced over the years to confirm and re-confirm the standardised and contemporary models of personality. However, it has also been pointed out in several instances (e.g., as far back as Allport, 1937, or for a more recent example see Conner et al., 2009) that the prevalent nomothetic approach to research essentially produces models that describe an “average individual” which, in truth, might never perfectly match any one person, as it could be enforcing an artificial mould that is not an accurate depiction of real people. Past findings have highlighted the presence of what has been called a “memory-experience gap” whereby participants will have stronger and more intense recollections of negative experiences than what was actually experienced at the time (Ellison et al., 2020; MacLaren Kelly et al., 2019; Urban et al., 2018), or more broadly the presence of extremity bias which leads individuals to think of past positive scenarios as better than they were, and negative scenarios as worse than they were (Ellison et al., 2020; Ben-Zeev et al., 2012). This may have translated into past findings having suffered from both the phenomena described above whereby participants overinflate their experiences (positive and negative), as well as having been impacted by memory processing impairments which have the potential to influence how one remembers a past event, feeling, or emotion, due to the requirement of accurate and full recall, retrieval, and integration of past experiences (Kahneman & Riis, 2005). It has also been pointed out that individuals who are asked to formulate an appraisal about their lives (which is often required in non-experience sampling SWB studies) may struggle to offer a suitable evaluation due to their lack of knowledge of the outcome or final consequences associated to a particular experience (Schooler et al., 2003). The present study used real time experience sampling data which bypasses these challenges, which may help explain why the findings were perhaps weaker than previous literature would lead to believe.

Given the extensive research over the past decades that has provided significant empirical data to consistently support the discriminant validity of these scales and traits, the explanation must not lie in the fact that these traits were potentially all identifying the same aspect of the affect variation, but rather that when combined with the demographic variables, some of the traits might have been overlapping with characteristics of one's lives.

Past research had important theoretical and methodological limitations. In addition to the previously mentioned theoretical questions surrounding the accuracy of models formulated based purely on the averaging of observations (i.e., nomothetic approach), other methodological limitations are noteworthy. Firstly, while ESM has become increasingly popular in recent years, the bulk of the studies published within psychology that use this methodology, still rely on aggregates and averaged responses for their analysis (Ellison et al., 2020), and many of these studies use small samples and/or very short time periods – for example, an ESM study from 2019 recruited 26 participants, of which five were excluded from data analysis (MacLaren Kelly et al.); another paper from 2022 used a sample of 144 university staff members, over the course of five days (Sawhney & Michel, 2022), with prompts at standardised times (i.e., when they finished work), rather than random moments.

The present study's results are encouraging and enhance the knowledge and literature regarding the relationship between personality and affective experiences by adding a layer of time variance that had not been analysed as such before. It establishes an undeniable link to past findings, and it highlights the need to further investigate the naturalistic events and experiences that occur in everyday life, and their connection to models and frameworks that are widely used in the field of psychology. The findings presented here emphasise that more research is necessary to determine the extent to which previous claims that stable and time invariant characteristics such as personality may explain approximately 50% of the variation in SWB (Lyubomirsky et al., 2005; Sheldon & Lyubomirsky, 2006). It may prove to be the case that a predictor such as personality may be a more accurate descriptor of the cognitive rather than the affective component of SWB. Past research has relied on a variety of scales and methods to research SWB (e.g., Delle Fave et al., 2011; Waldron, 2010; Donovan & Halpern, 2002; Kahneman et al., 1997), making it critical to further disentangle the components of SWB and fully understand how the time variation affects the relationship between variables. It is also important to establish the extent, both in intensity and length, to which daily and naturalistic experiences in individuals' lives have an overall impact in important life decisions (e.g., leaving a job, furthering one's personal development, changing careers, etc.). To understand behaviours, mechanisms, and environmental aspects that influence the affective component of subjective well-being and happiness is of great use as it has the potential to better inform, for example, the planning and development of interventions in organisations or more broadly, within larger communities.

### *4.4 Conclusion*

This study sought to address the research gap concerning the need for an advanced methodology (ESM) to be implemented in order to analyse whether the connection that has been reported between personality traits and affect (e.g., Costa & McCrae, 1980; Fleeson et al., 2002; Steel & Ones, 2002; Kardum, 1999; Mroczek & Almeida, 2004), would be confirmed if investigated using a methodology that incorporates the malleable and fluctuating nature of affective experiences in the study design and analysis, rather than forcing these observations into an aggregate or single observation format.

Using experience sampling allowed participant responses to translate into a more naturalistic depiction of affective experiences, producing longitudinal panel data. The main theoretical contribution of this study is the confirmation that the relationship between personality and affective experiences is indeed present, however, it may not be as strong as previously believed due to methodological constraints. The second contribution of this study is a methodological one. It demonstrates that an ESM study design paired with adequate multilevel modelling approaches is not only suitable to investigate previously tested theoretical models but can also be used to expand them by providing a more accurate way to investigate constructs that are, by nature, time varying. As a result, due to the time varying nature of these constructs, it stands to reason that using a methodology that is sensitive to their momentary changes without eliminating the richness of the data by converting it into an average value, research can further understand what the causes and effects are of certain life or daily events.

## Chapter 5: Study 2: Momentary happiness as an outcome of workplace situational and social variables

### *5.1 Introduction*

This study looked to investigate how everyday work tasks and social interactions in the workplace impact affective experiences at work. The existing literature suggests that being happy at work yields positive outcomes for the organisation (Field, Buitendach 2011, Fisher, 2010; Gavin & Mason, 2004; Money, Hillenbrand & Da Camara, 2008), although this research path is still rather limited (Oswald et al. 2015). It has essentially focused on individual attributes (e.g., personality) or work characteristics (e.g., job demands and resources) as the explanatory variables of how and why SWB at work might vary. Earlier research (for example, Lykken & Tellegen, 1996; Scwartz & Strack, 1991) attributed anywhere from 20 to 50% of variation in happiness to environmental aspects with reported evidence that situational aspects are rather important on how happy individuals are (Diener & Lucas, 2000) although this has not been investigated from a real time and disaggregated experiences point of view. The emphasis on the need to assess lived experiences in order to fully comprehend SWB by understanding how people experience their daily lives (and spend their time) has been called for before (Kahneman et al.,2004; Ellison, 2020; Sonnentag, 2015), yet it is still an area on which limited empirical evidence is available.

Multiple studies have since used experience sampling methodologies (ESM). Despite this step in the right direction, several of these studies demonstrate two broad and overarching limitations. The first is a theoretical limitation; many studies have focused on the general feeling of the sample, not necessarily on what may lead to SWB changes (short- or long-term), the important distinction between the stable component of SWB and the experiential and time varying component of affect, or addressed the limitation that when the attentional focus is on a past experience, it is possible that a participant’s response might not translate into the precise feelings experienced at the time (Dolan, 2014; Kahneman & Riis, 2005). This could be related to why a person might be less likely to assess themselves as “very happy” if they recently experienced mostly negative affect (Kahneman & Riis, 2005). The second is a methodological limitation; the most common methodologies (whether longitudinal or cross-section) have produced aggregate data, where the analysis employed involved the recourse to aggregate scores (Ellison et al., 2020), for example, in a longitudinal study where participants are asked to share their affective experience daily, this has traditionally been averaged into a single score per person, rather than analysed as multiple repeated observations. This is further emphasised by the notorious lack of studies that collect in-the-moment data (Kahneman & Krueger, 2006), or disaggregated information depicting momentary experiences or states (and not averages) (Ellison et al., 2020). While previous empirical findings propose that ratings of past affective experiences as means and frequencies are useful and more accurate than other types of estimates (e.g., rate of change occurred or how stable a perception was) (Stone et al., 2004), these studies still rely on averaged estimates themselves and do not measure momentary experiences (Ellison et al., 2020), making them liable to suffer from memory processing, storing or retrieval limitations, as well as more prone to extremity bias (MacLaren Kelly et al., 2019; Urban et al., 2018). Past evidence shows, for example, that individuals tend to have a negative recall bias concerning negative emotional experiences (e.g., Ellison et al., 2020; Ben-Zeev & Young, 2010), although these findings were not workplace specific.

Previous studies have shown that certain actions may be effective in increasing happiness, such as being optimistic; worrying less; doing acts of kindness; taking care of one’s social relationships; focusing on improving flow experiences; enjoying life’s joys; committing to goals; among others (Warner & Vroman, 2011). These actions are often done in the spur of the moment and the impact they may have had is easily forgotten. Traditional measures used in Psychology are frequently constructed and applied in ways that don’t capture these fluctuations.

In light of the limited data pertaining to experiencing affect (positive or negative) in different workplace contexts (e.g., what an individual is doing or who they are interacting with), combined with the potentially lower-than-theoriesed predictive ability of personality and other time stable variables with regards to momentary affective experiences, this study sought to address this gap in two ways. First, by utilising an experience sampling methodology. The ESM brings multiple advantages over retrospective methodologies. For example, the data collected is contextualized (i.e., timestamped) and enables the generation of dynamic portraits of how participants' functioning occurrs (Fisher & Boswell, 2016; Shiffman, Stone, & Hufford, 2008; Ellison et al., 2020). Secondly, with regards to the findings of study 1 that seem to indicate a lower than expected degree of affect variance explained by individual differences and dispositions, this study introduces time varying independent variables (work tasks and social interactions while working) as a proposed more suitable predictor of a time varying dependent variable (experienced affect).

Considering the need to investigate the effect time varying conditions at work, this study aimed to analyse if a combination of the type of activity that an individual is carrying out at work and who they interact with at that time might be a better predictor of affect experiences in the workplace. Classical occupational psychology theories such as Karasek's popular Job Demands-Control model (JDC, 1979) and job content questionnaire (1985) were early steps into the notion that the characteristics of occupational lives having relevant impacts that must be understood, later leading to the further development of this model into the Job Demands-Resources (Bakker & Demerouti, 2007). These models and the theoretical underpinnings they set have been widely used as inspiration for research since. Boschman et al. (2017) found that when using a longitudinal dataset, intra-individual variability was seen for task specific work ability which indicates that if the ability perception varies per task, then how one feels while performing distinct activities can reasonably be expected to also show differences in affect, thus there is a need to further investigate the effect that performing different types of work tasks has on how the individual feels while performing different tasks. Chamebl et al. (2017) conducted a study that found that the participants' perceptions of their JD-C characteristics were significantly related to well-being, albeit measured with a cross-sectional design. Shin et al. (2021) found that task creativity and variety, assessed with five dichotomous scales involving: cognitive demand; non-monotonicity, non-repetitiveness, complexity, learning new things, and solving unforeseen problems, and one likert scale: applying own ideas (rated one through five), acted as protective layers against negative job characteristics such as long working hours and working night shifts, further supporting the proposition that the activities that individuals engage in while at work are a key variable to be investigated in relation to affective experience.

Another key aspect to consider with regards to the workplace variables that are malleable (i.e., time varying) is the social interactions that occur in the workplace. Research has shown that isolation in the context of work can be due to effective physical distance (Bartel et al., 2012) or due to a perception that there is distance from others (Marshall et al., 2007), with the negative potential outcomes of leading to feelings of being undervalued, not appreciated, and with a negative impact on organisational variables, including well-being and job satisfaction (D'Oliveira & Persico, 2023; Riggle, 2007; Kurland & Cooper, 2002), among others. An important aspect has to do with who the interactions occur with; it is plausible to presume that interacting with people with whom a closer connection exists (e.g., a friend) might have a distinct impact to those with whom a merely transaction interaction takes place (e.g., a customer). The quality of social relationships at work has been found to be positively related to better mental and physical health (Rydstedt et al., 2012), thus further supporting the relevance of considering social interactions at work as a key antecedent of affective experiences at work. These distinctions are suggested in D'Oliveira and Persico (2023) as needing further development namely by better investigating the types of social relationships, support roles, and well-being.

From an occupational psychology perspective, there are immense applications for this knowledge. For example, if there is a need to investigate what might help explain a progressively lower engagement of the company's teams on optional social gatherings, or a progressively higher turnover ratio which may prove costly for the company, this calls for the application of a measure and methodology that has enough sensitivity to capture short-term changes and their impact on participants. Sonnentag (2015) proposes that the SWB studies conducted using within-person designs, usually attribute the fluctuations seen in SWB to the immediate events that the participant has experienced. The author explains that SWB not being stable directly implies that it suffers both short-term fluctuations as well produces longer-term increases or decreases in SWB over periods of months or years. As a result, the two primary hypotheses that this study tested were:

H1: Different work activities and tasks will predict affect experience perceptions.

H2: Momentary workplace interactions will predict affect experience perceptions.

### *5.2 Results*

The data was cleaned and analysed with Stata/MP 17.0. As such, those instances of the data were removed from the analysis. A sample of N=111 individuals from whom 1,855 datapoints of in-the-moment-data, while at work, were obtained. The average number of responses per participant was 16.7 (only complete datasets were considered). The participants' age ranged between 19 and 75 years old ($M_{age}$= 36.14, $SD_{age}$= 8.04), and it includes 59 females and 52 males.

The work tasks being performed at the time of each experience sampling moment were divided into broad categories to allow for their use across professions, industries, and seniority levels. Specific tasks were avoided (e.g., "parent-teacher meeting", "writing software code", "analysing laboratory samples", etc.) and broader options such as "I'm in a meeting" or "I'm doing something that I do frequently /

infrequently" were preferred. In total, the participants were able to select multiple choices and combinations from a list of six categories (see table 6 below). Relibilities were calculated for the overall SPANE scale (SPANE balance, which was once again found to be highly reliable, with a cronbach's α = .91) and its subscales (SPANE-PA, α = .93 and SPANE-NA, α = .89).

**Table 6**

*Affect score per work task grouping.*

| **Work tasks** | **Stats** | **Positive Affect** | **Negative Affect** | **Affect Balance** |
|---|---|---|---|---|
| break | $N_{obs}$ | 134 | 134 | 134 |
| | Mean | 22.07 | 8.25 | 13.83 |
| | SD | 5.49 | 3.45 | 7.38 |
| call | $N_{obs}$ | 41 | 41 | 41 |
| | Mean | 21.51 | 8.95 | 12.56 |
| | SD | 5.07 | 3.46 | 7.37 |
| meeting | $N_{obs}$ | 148 | 148 | 148 |
| | Mean | 22.16 | 8.76 | 13.40 |
| | SD | 4.59 | 3.76 | 7.04 |
| procrastinating | $N_{obs}$ | 69 | 69 | 69 |
| | Mean | 20.81 | 8.75 | 12.06 |
| | SD | 4.40 | 3.07 | 5.93 |
| Unusual task | $N_{obs}$ | 282 | 282 | 282 |
| | Mean | 20.83 | 9.67 | 11.17 |
| | SD | 5.72 | 4.55 | 8.86 |
| Usual task | $N_{obs}$ | 1175 | 1175 | 1,175 |
| | Mean | 21.75 | 8.59 | 13.16 |
| | SD | 5.03 | 3.69 | 7.37 |
| Total | $N_{obs}$ | 1849 | 1849 | 1,849 |
| | Mean | 21.63 | 8.76 | 12.87 |
| | SD | 5.13 | 3.81 | 7.58 |

The category that showed the highest level of positive affect was "meetings" ($M$ = 22.16, $SD$ = 4.59), whereas the one that reported the lowest positive affect experienced by the workers was "procrastination" ($M$ = 20.81, $SD$ = 4.40). The activity that generated the highest score for experienced negative affect was "unusual tasks", i.e., those that participants do not commonly perform as part of their work ($M$ = 9.67, *SD* = 4.55), and the lowest negative affect was reported when on a “break” from work tasks (*M* = 8.25, *SD* = 3.45).

Another time varying variable this study relies on is the social interaction aspects of the context of work. Table 7 displayed below shows the means and standard deviations for the positive, negative and affect balance scores depending on who the participants were interacting with in the moment of each experience sampling occasion. Participants were able to select multiple responses from the list of categories with various instances of professional (e.g., supervisor, client) and personal options (e.g., children, friends). The social context that reveals the highest positive affect (*M* = 24.17, *SD* = 4.42) and lowest negative affect (*M* = 8.38, *SD* = 3.04), on average, is a combination of people who have professional and personal relationships with the participant, whereas the lowest positive affect (*M* = 20.06, *SD* = 5.05) and highest negative affect (*M* = 9.24, *SD* = 4.02) is seen when the respondents are on their own.

**Table 7**

*Affect scores per social situation*

| Social situation | Stats | Positive Affect | Negative Affect | Affect Balance |
|---|---|---|---|---|
| Alone | $N_{obs}$ | 608 | 608 | 608 |
| | Mean | 20.06 | 9.24 | 10.82 |
| | SD | 5.05 | 4.02 | 7.50 |
| Mixed professional and personal | $N_{obs}$ | 89 | 89 | 89 |
| | Mean | 24.17 | 8.38 | 15.79 |
| | SD | 4.42 | 3.04 | 6.19 |
| Personal relationships | $N_{obs}$ | 76 | 76 | 76 |
| | Mean | 22.55 | 8.93 | 13.62 |
| | SD | 5.69 | 3.83 | 8.60 |
| Professional relationships | $N_{obs}$ | 851 | 851 | 851 |
| | Mean | 21.91 | 8.60 | 13.31 |
| | SD | 5.07 | 3.87 | 7.68 |
| Total | $N_{obs}$ | 1624 | 1624 | 1,624 |
| | Mean | 21.37 | 8.85 | 12.53 |
| | SD | 5.18 | 3.89 | 7.71 |

There are different statistical procedures and tests that inherently address the issues posed by panel data, including the fact that there is no independence of the standard error terms or that the dataset may be unbalanced, as is the case with the present study. Given the type of panel data being studied, and the aim of this research, the appropriate models are fixed effects (FE) or random effects (RE) models. To ensure that the correct model was used, Hausman tests were conducted (Hausman, 1978) to confirm whether the choice of a RE model was appropriate over a FE model. Both FE and RE models were fitted to the data to confirm whether the individual level effects are sufficiently captured by a FE model which assumes that they are constant; or whether these individual effects are random (following a normal distribution).

*5.2.1 Positive affect predicted by work tasks*

A Hausman test was conducted, and the results suggest that when both models are compared, a regression using a Random Effects model is the appropriate choice ($\chi^2$ = 2.91, $p$ = .71). The RE model estimates that the effect of work task characteristics on positive affect is responsible for nearly 49% of the variations of PA scores. A precise estimate will be given below for each of the models calculated.

Given the nature of categorical variables (i.e., the outcome of each variable is binary – the participant either is or is not performing a particular task) and how multilevel random effects models run, one of the categories is considered as the starting point for the analysis, i.e., the model presumes that this base variable is zero (not present), while estimating the effect of the remaining variables. Since the descriptive statistics identified procrastination as the task that scored lowest, on average, for positive affect, a model was estimated where this was the base variable. The model estimates the specific effects of the remaining five categories: “taking a break”, “performing a usual task”, “performing an unusual task”, “being in a meeting”, and “being on a call”. The largest effect on positive affect is predicted by “taking a break” and “being in a meeting” which increases the positive affect score by 1.50 points

($z$ = 2.54, $p$ = .01 and $z$ = 2.56, $p$ = .010, respectively) each – this is to say that positive affect might change from 20 points when not taking a break to 21.5 points while taking a break. Performing usual or unusual tasks and being in calls are non-significant predictors of changes in positive affect. This model estimated that these work tasks categories explain 48.8% of the positive affect variance.

### *5.2.2 Negative affect predicted by work tasks*

A Hausman test was conducted, and the results suggest that when both models are compared, a regression using a Random Effects model is the appropriate choice ($\chi^2$ = .50, $p$ = .48).

The model to be fitted follows a similar logic identified above; "taking a break" being the category that produced the lowest negative affect scores was the categorical variable that was omitted from the model. The remaining five categories were included. The only significant predictor of negative affect was "performing unusual tasks", which increases the negative affect score by 0.89 points ($z$ = 2.87, $p$ = .004) (e.g., from 20 to 19.11 points). Procrastinating, being in meetings or calls, or performing usual tasks are not significant predictors of the negative affect score at work. This model is estimated to explain 53.3% of the variance in negative affect at work.

### *5.2.3 Affect balance predicted by work tasks*

Since work tasks were shown to predict of both positive and negative affect, and the models produced so far were estimated to explain a sizeable portion of the variation in the affective scores, a model was fitted to determine the suitability of work tasks to predict affect balance. A Hausman test was used to confirm the that a random effects model was suitable ($\chi^2$ = .59, $p$ = .44). This model shows that the strongest predictors of affective balance changes at work are the performance of unusual tasks, which causes the affect balance score to decrease by 1.99 points ($z$ = -3.16, $p$ = .002), and the performance of usual tasks that leads to a decline of 1.17 points in the affect balance score ($z$ = -2.18, $p$ = .29). An aspect worth of note is that being in calls is approaching significance (*coeff.* = -2.03, $z$ = -1.93, $p$ = .053), as is procrastinating (*coeff.* = 1.66, $z$ = -1.89, $p$ = .059). Participating in meetings does not have a significant effect on affect balance changes and taking a break from work was used as the starting point for this model and as such there is no regression coefficient for this category. This model is estimated to account for 50.4% of the affect balance variation based on work task.

*5.2.4 Positive affect predicted by social relationships at work*

A Hausman test was conducted, and the results suggest that when both models are compared, a regression using a Fixed Effects model is the appropriate choice ($\chi^2$ = 5.24, $p$ = .022).

A model with the various categories of work interactions was fitted. Since being alone scored lowest, on average, for positive affect, we will estimate a regression model without this variable to determine how the remaining categories of social interactions predict positive affect. The largest effect on positive affect is predicted by working while interacting with someone with whom the participant has a personal relationship (this could refer to friends, family, etc.) which increases positive affect scores by 1.37 points ($t$ = 2.91, $p$ = .004). Having interactions with a mixed group of personal and professional relationships significantly increases the PA score by 1.35 points ($t$ = 2.32, $p$ = .02), as does being in situations where the interactions involve professional relationships only, which improve positive affect by 0.87 points ($t$ = 4.11, $p$ < .001). This model estimates that these categorical social relationships explain 49.9% of the positive affect variance.

*5.2.5 Negative affect predicted by social relationships at work*

A model where negative affect is predicted by social relationships at work does not appear to be an interesting option since omnibus tests for both the FE and RE models shows that support for the hypothesis that at least one coefficient is different from zero is not obtained (*F(3,1723)* = .59, *p* = .6194 and *W* = 1.66, *p* = .6461, respectively). It became clear that the data indicates that social relationships at work are not statistically good predictors of changes in negative affect, and no significant coefficients that differed from zero were identified.

*5.2.5 Affect balance predicted by social relationships at work*

A Hausman test was conducted, and the results suggest that when both models are compared, a regression using a Fixed Effects model is the appropriate choice ($\chi^2$ = 4.73, *p* = .030).

To understand the types of social relationships at work that may be the most notable predictors of affective balance, a model was fitted where each category of relationship was included as a distinct predictor variable, excluding the category that had the lowest mean affect balance – being alone. The FE model reveals that being around those with whom the participants have either personal or professional relationships were significant and positive predictors of affect balance that will increase the score by 1.58 points (*t* = 2.23, *p* = .03) and 0.97 points (*t* = 3.06, *p* = .002), respectively. A mixed group of people from both worlds, personal and professional, is not a significant predictor.

*5.2.6 Combined models of activities and social interactions as predictors of affective experience*

Finally, models were computed to test the suitability of a model which includes both independent variables – work activities, and workplace social interactions. To verify if a FE or RE model was appropriate for the model to predict positive affect, a Hausman test was conducted, and the results suggest that when both models are compared, a regression using a Fixed Effects model is the appropriate choice ($\chi^2$ = 18.56, *p* = .017). This model was estimated to explain 50.01% of the positive affect variation, and all activities except “being in a meeting”, along with all social interaction categories were significant predictors of positive affect. Table 8 below shows a summary of the regression results.

**Table 8**

Composite Positive Affect regression with activities and interactions.

| **Fixed effects** | **Coefficient** | ***SE*** | ***t*** | **95% CI** | | ***p*** |
|---|---|---|---|---|---|---|
| | | | | ***LL*** | ***UP*** | |
| On a call | -1.65 | 0.73 | -2.26 | -3.08 | -0.22 | 0.02 |
| In a meeting | -0.27 | 0.49 | -0.56 | -1.24 | 0.69 | 0.58 |
| Procrastinating | -1.42 | 0.60 | -2.39 | -2.59 | -0.26 | 0.02 |
| Performing unusual task | -1.27 | 0.43 | -2.98 | -2.11 | -0.43 | 0.00 |
| Performing usual task | -0.94 | 0.36 | -2.59 | -1.66 | -0.23 | 0.01 |
| | | | | | | |
| Mixed personal-professional | 1.33 | 0.59 | 2.25 | 0.17 | 2.48 | 0.03 |
| Personal relationship | 1.30 | 0.47 | 2.75 | 0.38 | 2.23 | 0.01 |
| Professional relationship | 0.85 | 0.22 | 3.89 | 0.42 | 1.28 | 0.00 |
| | | | | | | |
| Constant | 21.96 | 0.36 | 61.02 | 21.26 | 22.67 | 0.00 |
| SD residuals within groups | 3.71 | | | | | |
| SD overall error | 3.71 | | | | | |
| rho | 0.5001 | *(Total DV variance explained by model)* | | | | |

Note: Number of groups = 111, number of observations = 1,831. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

To analyse the suitability of the combined model’s predictors in relation to negative affect, a Hausman test suggested that a regression using a Random Effects model was appropriate ($\chi^2$ = 3.87, $p$ = .868). This model was estimated to explain 53.17% of the negative affect variation, with performing unusual tasks significantly predicting an increase in NA. Table 9 below shows a summary of the regression results.

**Table 9**

Composite Negative Affect regression with activities and interactions.

| Fixed effects | Coefficient | *SE* | *t* | 95% CI *LL* | 95% CI *UP* | *p* |
|---|---|---|---|---|---|---|
| On a call | 0.54 | 0.54 | 0.99 | -0.52 | 1.59 | 0.32 |
| In a meeting | 0.24 | 0.36 | 0.66 | -0.47 | 0.95 | 0.51 |
| Procrastinating | 0.21 | 0.44 | 0.48 | -0.65 | 1.07 | 0.63 |
| Performing unusual task | 0.98 | 0.31 | 3.10 | 0.36 | 1.59 | 0.00 |
| Performing usual task | 0.28 | 0.27 | 1.05 | -0.24 | 0.81 | 0.29 |
| Mixed personal-professional | 0.23 | 0.43 | 0.53 | -0.62 | 1.07 | 0.60 |
| Personal relationship | -0.22 | 0.35 | -0.62 | -0.90 | 0.47 | 0.54 |
| Professional relationship | -0.14 | 0.16 | -0.87 | -0.46 | 0.18 | 0.39 |
| Constant | 8.84 | 0.39 | 22.81 | 8.08 | 9.60 | 0.00 |
| SD residuals within groups | 2.93 | | | | | |
| SD overall error | 2.75 | | | | | |
| rho | 0.5317 | *(Total DV variance explained by model)* | | | | |

Note: Number of groups = 111, number of observations = 1,831. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

To analyse the combined model predictors in relation to affect balance, a Hausman test suggested that a regression using a Random Effects model was appropriate ($\chi^2 = 14.14$, $p = .078$). This model was estimated to explain 48.23% of the affect balance variation, with all activities except “being in a meeting”, along with all social interaction categories shown to be significant predictors of affect balance. However, contrary to what was seen for PA, all work activities produce a negative impact on affect balance scores, and social interactions a positive one. Table 10 shows a summary of the regression results.

**Table 10**

*Composite Affect Balance regression with activities and interactions.*

| Fixed effects | Coefficient | *SE* | *t* | 95% CI *LL* | 95% CI *UP* | *p* |
|---|---|---|---|---|---|---|
| On a call | -2.14 | 1.09 | -1.96 | -4.27 | 0.00 | 0.05 |
| In a meeting | -0.59 | 0.73 | -0.81 | -2.02 | 0.84 | 0.42 |
| Procrastinating | -1.67 | 0.89 | -1.89 | -3.41 | 0.06 | 0.06 |
| Performing unusual task | -2.30 | 0.63 | -3.62 | -3.54 | -1.05 | 0.00 |
| Performing usual task | -1.22 | 0.54 | -2.25 | -2.29 | -0.16 | 0.02 |
| | | | | | | |
| Mixed personal-professional | 1.38 | 0.86 | 1.60 | -0.31 | 3.08 | 0.11 |
| Personal relationship | 1.57 | 0.70 | 2.23 | 0.19 | 2.94 | 0.03 |
| Professional relationship | 1.08 | 0.33 | 3.32 | 0.44 | 1.72 | 0.00 |
| | | | | | | |
| Constant | 12.75 | 0.74 | 17.13 | 11.30 | 14.21 | 0.00 |
| SD residuals within groups | 5.35 | | | | | |
| SD overall error | 5.54 | | | | | |
| rho | 0.4823 | *(Total DV variance explained by model)* | | | | |

Note: Number of groups = 111, number of observations = 1,831. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

In summary, looking at the results of the combined models that estimated the degree to which work tasks and social interactions – together – were able to explain affect variance, the overall ability of these models to explain around 50% of the variance in affect was retained, with all the work tasks except “being in a meeting” and all social interactions being significant predictors of affect (positive and balance), and only the performance of unusual tasks was shown to significantly impact negative affect. These results once again support the proposition to rely on time varying aspects of work to predict affective experiences during working hours, supporting both hypotheses tested in this study.

### *5.3 Discussion*

This study's aims were to investigate whether momentary, real-time, affective experiences could be adequately predicted by momentary, real-time, work-related factors such as the activities being engaged in (H1) and the social interactions taking place (H2). This was done by investigating the impact of six categories of work-related tasks and four categories of social interaction groups on experienced affect. It was hypothesised that both time varying independent variables (activities as well as the social interactions) would predict how the individuals experience affect at work.

Multilevel longitudinal fixed and random effects regression models were computed to determine the extent to which the time varying independent variables were suitable estimators of positive affect (PA), negative affect (NA), and affect balance (AB) – the time varying dependent variables which vary between and within subjects, as well as through time. Results showed that the models to predict variations in positive, negative and affect balance explained between 48.8% and 53.3% of the variation in the dependent variable. Of the six work activities categories used in this study, four were revealed to be significant predictors of affect experiences at work – taking breaks (PA), participating in meetings (PA), performing unusual tasks (NA and AB), and performing usual tasks (AB). Social interactions at work, divided in four categories – alone, personal relationships, professional relationships, mixed personal and professional relationships – was shown to be a significant predictor of affective experiences, with personal relationships (both exclusively, and in a mixed scenario) being responsible for predicting PA in a model that sees social relationships as being able to explain 49.9% of the variance in PA. The affect balance score was significantly predicted by personal and professional relationships (separately, not mixed), with an overall 51.61% of variance of AB being explained by this model. The results show support for both hypotheses being tested – activities that individuals engage in at work and those they interact with are significant predictors of the affective experience perceptions.

The proportion of affect variation explained by these models (approximately 50% throughout) is both in line with past research and indeed rather interesting considering that previous suggestions (e.g., Lykken & Tellegen, 1996; Scwartz & Strack, 1991) indicated that as little as 20% up to 50% of variation in SWB might be explained by context related factors or intentional action. The fact that the results strongly lean towards the upper limit of the interval is cause to believe that more research is necessary, including by introducing more granularity in the independent variable levels.

The implication of the results obtained here is also in line with recent research sustaining that workplace isolation brings unwanted and adverse impacts to the lives of the employees in any work environment (D'Oliveira & Persico, 2023), rather than due to particular workplace characteristics (see for example, Mulki et al., 2008; Mulki & Jaramillo, 2011; Bartel et al., 2012; Golden et al., 2008; Jackowska & Lauring, 2021). The fact that in the positive and affect balance individual as well as combined models, the social interaction predictors were significant and positive, i.e., contribute to an increaIe in the affect score, seems to indicate that this is so regardless of the more formal task-based characteristics of the situations taking place. However, it is important to note that the negative affect models (individual and combined) did not provide statistically significant reasons to believe that being in situations where others are present might decrease the NA score. Based on prior literature and empirical evidence, we might suspect that this could be an indication that the participants in the sample being examined might not have an overly high level of loneliness to begin with, since it has been suggested that the effect of loneliness at work is all the more pervasive for those individuals who already felt lonely and that these expressed feelings of loneliness in the workplace might be contagious from employee to employee (see for example Jones, 1981; Wright, 2015; Cacioppo et al., 2009).

The finding that performing unusual tasks has a significant negative effect on PA and BA and a positive effect on NA is likewise worth of note. While job demands have not been framed in exactly this formulation of "unusual tasks", it is reasonable to assume that if a task is not part of an employee's everyday demands and job description, it is likely to require additional effort, mental capacity, and focus when they do come up – infrequently – as there is no place for habituation and task specific experience to lighten the burden of the performance of these types tasks.

A limitation of the present study is tied to the granularity used in the independent variables categories. Due to the nature of the study's recruitment aims (i.e., wide-reaching, very few restrictions – in fact, just one restriction: participants must have been over the age of 18 years old), the experience sampling items were constructed such that there would be no impediment to any participants sharing their everyday experiences. This led to, for example, opting for generally formulated items (e.g., "I'm in a meeting") as opposed to much more specific items that would only be suitable in some contexts (e.g., "I'm in a product meeting" / "I'm at a conference" / "I'm in a parent-teacher meeting", and so forth). Future studies where meaningful granularity could be added would be of great interest as it might contribute to the understanding of the underlying causes of SWB, for example, per industry or even in particular cultural settings (e.g., more meeting prone or averse cultures; more socially adept cultures versus more individualistic cultures; etc.). Similar reasoning can be applied to the social interactions categories, where an improvement and interesting proposal for future research lies in understanding the extent of the interactions, including to understand the distinction between "mixed scenarios". For example, in the present study it was not possible to distinguish between situations in which the participants who indicated that they are interacting with a co-worker as well as a friend refer to the same and only person (i.e., they consider their co-worker a personal friend), or whether they are interacting with distinct people (e.g., working from home, sharing a physical space with a friend, and interacting with co-workers online). Some of these considerations were not at the foremind when the study was planned and designed, a full two years before the COVID-19 pandemic. However, it has since been established that many workplaces have permanently altered what is considered “normal” working situations, and as such research questions that focus on understanding these nuances and distinctions are all the more relevant.

### *5.4 Conclusion*

This study sought to investigate whether momentary, real-time, affective experiences could be adequately predicted by momentary, real-time, work-related factors such as the activities being engaged in (H1) and the social interactions taking place (H2). The study’s results revealed that both of these variables are suitable predictors of momentary affect – both as a single-variable model, as well as in a model that combines both these time varying variables.

The implementation of a ESM methodology was a highly effective choice and indicated that momentary experiences can be appropriately investigated by account for and retaining all the richness of data that is produced by longitudinal panel data. It further emphasises the need for more research to be conducted in such a way – without the recourse to aggregates.

This study offers an important theoretical and methodological contribution to the field of occupational psychology by suggesting that malleable and time sensitive independent variables might be a more appropriate choice for a study design when the intention is to understand what might be behind the different observations of a dependent variable that is itself also variable in time. Regardless of whether the dependent variable also varies within or between participants. In either case, time varying independent variables are appropriate choices, and their value is increased by not aggregating the resulting observations to perform the data analysis. Instead, multilevel longitudinal modelling should be used to account for the non-independence of observations, as well as the potential presence of random intercepts or not, fixed, or varying slopes, in the models created to estimate the effect that the data showcases.

# Chapter 6: Study 3: Momentary happiness as an antecedent of productivity at work

## *6.1 Introduction*

To continue investigating the relevance and suitability of using time varying and malleable variables measured through an ESM methodology, this study's main aim is to confirm whether this methodology may be used to adequately provide support to the theoretical literature that suggests that SWB is an antecedent of organisational productivity (Diener et al, 2018). Despite extensive research on productivity as an important organisational outcome, its investigation from a longitudinal and non-aggregate perspective is still underdeveloped (Oswald et al., 2015), and specifically as an outcome of SWB (Diener et al., 2018).

The broad literature primarily leans in the direction that there is a causal relationship between SWB and productivity, i.e., that happier employees lead to positive organisational outcomes (e.g., Krekel et al., 2019; Harter et al., 2010; Harter et at., 2002; Field & Buitendach, 2011), however, it is a topic that has proven challenging (Diener et al., 2018), partly due to different definitions of productivity both at the individual and organisational level (e.g., higher wages equated to higher productivity; subjective and objective reports of performance; company performance; etc.). Amongst the findings of past research, it was found that trait but not state affect helped explain productivity over time (Wright & Staw, 1999); if this were an accurate representation of the relationship between well-being as an antecedent of productivity, then it would not be plausible to expect a time varying measure, such as transient affective experiences as measured within the work of this thesis, to be a good predictor or productivity. However, this is not a well enough researched area and as such it is necessary to further understand the mechanisms that help explain why and how happier people to become more productive than those who are less happy (Diener et al., 2018) which is the predominant view.

One of the challenges in analysing and interpreting the literature in this area is the multitude of measures and indicators used – making it difficult to establish straightforward and clear comparisons (Tenney et al., 2016). These authors point out that despite the encouraging longitudinal evidence on some indicators, a causal relationship of SWB and performance has not been possible to demonstrate so far. A relevant aspect to consider is the suggestion that high SWB may be a better predictor of socially inclined tasks (e.g., making a good impression on someone) or to tackle complicated tasks, rather than for an immediate improvement concerning a given cognitive tasks of average complexity (Tenney et al., 2016; Oswald et al., 2015).

Oswald et al. (2015) highlight the fact that how individuals allocate their time to various activities is related to their SWB, generally opting for spending more time on interesting tasks (Seo et al., 2010). Similarly, Shi et al. (2013) found that when mental health was poor, the self-reported performance metrics were also reduced, and negative affect overall seems to be related to decreased performance (Foo et al., 2009). However, most of the studies conducted looking into these relationships were not sensitive to the within-individual fluctuations (i.e., longitudinal panel data) (Sonnentag, 2015).

In this study, productivity is divided into self-reported performance ratings concerning in-role performance (IRP) and extra-role performance (ERP). The former has to do with the tasks and endeavours that one is usually expected to do as part of a contractual  job; it is a type of performance that is primarily prescribed to an employee and is not optional (IRP). The latter (ERP) can be seen as organisational citizenship behaviours (Sonnentag, 2015), whereby this type of performance is usually optional, not prescribed, and tends to be seen as a desirable behaviour, but not a contractual obligation.

Given the lack of well-established findings in the literature regarding the mechanism(s) that explains the connection between SWB and performance (e.g., Bryson et al., 2017), and particularly the distinction between in-role and extra-role performance, this study’s hypotheses are, cautiously, that performance may be predicted by momentary affective experiences which can be construed as transient affect, activities being partaken in, and social interactions. Since the previous study showed a considerable percentage of affective experience variation to be predicted by workplace factors, it is plausible that the same aspects might help explain self-perceptions of productivity.

H1: Affective experiences (time varying predictor) will help explain variations in self-reported real-time perceptions of productivity (time varying outcome), specifically:

H1a: Positive affect predicts higher performance scores than negative affect.

H1b: Affect experiences are stronger predictors of extra-role than in-role performance.

H2: Contextual work-related tasks data (time varying predictor) will help explain variations in self-reported real-time perceptions of productivity (time varying outcome).

H2a: In-role performance is likely to be predicted by tasks that directly relate to the performance of one’s job (e.g., “usual or unusual tasks” instead of “being on a break”).

H2b: Contextual work-related tasks are likely to be better predictors of in-role than extra-role performance.

H3: Social interactions (time varying predictor) will help explain variations in self-reported real-time perceptions of productivity (time varying outcome)

H3a: Social interactions will predict extra-role performance better than in-role performance.

### *6.2 Results*

The data was cleaned and analysed with Stata/MP 17.0. Since this study uses a naturalistic approach to data collection via experience sampling at random times of the day, some data was collected at times when participants were not working. All non-work responses, or participants with fewer than five moments of experience sampling were removed from the analysis. The sample for analysis consists of N=111 individuals and 1855 datapoints of in-the-moment-data, while at work. The participants were aged 19 to 75 years old ($M_{age}$= 36.14, $SD_{age}$= 8.04), with 59 females and 52 males.

Productivity was self-assessed as both that which is related to core fulfilment of one's role obligations and expectations (in-role performance) and that which is related to the fulfilment of additional tasks that do not form part of contractual obligations or role expectations, generally not prescribed but beneficial to the organisation (extra-role performance). The tables below summarise the descriptive statistics pertaining to this study's time varying independent and dependent variables that are measured on a scale (positive, negative, and affect balance, and performance), as well as the time varying dependent variables: productivity (in-role and extra-role). Table 11 provides an overview of the average scores for the continuous outcomes independent variables: positive, negative and affect balance scores, and each individual affective experience scale. A closer look reveals that there is a larger dispersion of positive ($SD$ = 5.13) than negative ($SD$ = 3.82) affect scores, and that negative scores are rather low ($M$ = 8.77, $SD$ = 3.82) which could indicate that the sample represents more varied positive affect experiences at work as well as positive tendency overall (i.e., more participants likely to feel more frequent positive than negative affect).

**Table 11**

*Descriptive statistics for positive, negative, and affect balance.*

| Variable | $N_{obs}$ | Mean | SD |
|---|---|---|---|
| Positive affect | 1,855 | 21.62 | 5.13 |
| Negative affect | 1,855 | 8.77 | 3.82 |
| Affect balance | 1,855 | 12.86 | 7.57 |
| Content | 1,843 | 3.44 | 1.05 |
| Good | 1,850 | 3.84 | 0.85 |
| Happy | 1,843 | 3.62 | 1.00 |
| Joyful | 1,845 | 3.37 | 1.07 |
| Pleasant | 1,848 | 3.56 | 0.97 |
| Positive | 1,853 | 3.87 | 0.84 |
| Angry | 1,842 | 1.35 | 0.72 |
| Afraid | 1,844 | 1.64 | 0.97 |
| Bad | 1,850 | 1.44 | 0.74 |
| Negative | 1,851 | 1.52 | 0.80 |
| Sad | 1,843 | 1.37 | 0.72 |
| Unpleasant | 1,845 | 1.48 | 0.80 |
| Tired | 1,480 | 2.61 | 1.28 |

With regards to the categorical independent variables – work tasks and social interactions at work – we can see from the table 12 that the work tasks category that showed the highest level of positive affect was “meetings” (*M* = 22.16, *SD* = 4.59), whereas the one that reported the lowest positive affect experienced by the workers was “procrastination” (*M* = 20.81, *SD* = 4.40). The highest score for experienced negative affect was reported for the moments in which the participants were engaged in “unusual tasks” (those that are not commonly performed as part of their roles (*M* = 9.67, *SD* = 4.55)), and the lowest negative affect was reported when on a “break” from work tasks (*M* = 8.25, *SD* = 3.45). It is interesting to note that participants seemed to effectively distinguish between moments of necessary and relevant pauses from their work (“taking a break”), and moments of procrastination (i.e., avoiding work). This differentiation is emphasised by the fact that procrastination does not seem to generate as much positive affect as other tasks (*M* = 20.81, *SD* = 4.40), but it also does not seem to produce the highest amount of negative affect (*M* = 8.75, *SD* = 3.07), whereas taking a break were the moments when participants reported the lowest average negative affect overall (*M* = 8.25, *SD* = 3.45), and yet still higher positive affect (*M* = 22.07, *SD* = 5.49) than while procrastinating.

**Table 12**

*Affect scores per activity and interaction.*

| | Stats | Positive Affect | Negative Affect | Affect Balance |
|---|---|---|---|---|
| **Work tasks** | | | | |
| | $N_{obs}$ | 134 | 134 | 134 |
| Taking a break | Mean | 22.07 | 8.25 | 13.83 |
| | SD | 5.49 | 3.45 | 7.38 |
| | $N_{obs}$ | 41 | 41 | 41 |
| On a call | Mean | 21.51 | 8.95 | 12.56 |
| | SD | 5.07 | 3.46 | 7.37 |
| | $N_{obs}$ | 148 | 148 | 148 |
| In a meeting | Mean | 22.16 | 8.76 | 13.4 |
| | SD | 4.59 | 3.76 | 7.04 |
| | $N_{obs}$ | 69 | 69 | 69 |
| Procrastinating | Mean | 20.81 | 8.75 | 12.06 |
| | SD | 4.4 | 3.07 | 5.93 |
| | $N_{obs}$ | 282 | 282 | 282 |
| Unusual task | Mean | 20.83 | 9.67 | 11.17 |
| | SD | 5.72 | 4.55 | 8.86 |
| | $N_{obs}$ | 1175 | 1175 | 1,175 |
| Usual task | Mean | 21.75 | 8.59 | 13.16 |
| | SD | 5.03 | 3.69 | 7.37 |

| | Stats | Positive Affect | Negative Affect | Affect Balance |
|---|---|---|---|---|
| **Social interactions at work** | | | | |
| Alone | N obs | 608 | 608 | 608 |
| | Mean | 20.06 | 9.24 | 10.82 |
| | SD | 5.05 | 4.02 | 7.5 |
| Mixed professional and personal | N obs | 89 | 89 | 89 |
| | Mean | 24.17 | 8.38 | 15.79 |
| | SD | 4.42 | 3.04 | 6.19 |
| Personal relationships | N obs | 76 | 76 | 76 |
| | Mean | 22.55 | 8.93 | 13.62 |
| | SD | 5.69 | 3.83 | 8.6 |
| Professional relationships | N obs | 851 | 851 | 851 |
| | Mean | 21.91 | 8.6 | 13.31 |
| | SD | 5.07 | 3.87 | 7.68 |

Another time varying variable this study relies on is the social interaction aspects of the context of work. The social context that reveals the highest positive affect (*M* = 24.17, *SD* = 4.42) and lowest negative affect (*M* = 8.38, *SD* = 3.04), on average, is a combination of people who have professional and personal relationships with the participant, whereas the lowest positive affect (*M* = 20.06, *SD* = 5.05) and highest negative affect (*M* = 9.24, *SD* = 4.02) is seen when the respondents are on their own.

**Table 13**

*Descriptive statistics for self-reported perceived productivity.*

| Productivity | N obs | Mean | SD |
|---|---|---|---|
| IRP score | 663 | 13.94 | 2.83 |
| IRP Objectives | 664 | 4.59 | 1.07 |
| IRP Requirements | 665 | 4.64 | 1.04 |
| IRP Tasks | 664 | 4.72 | 1.00 |
| ERP score | 676 | 11.01 | 3.69 |
| ERP Do more | 677 | 3.98 | 1.40 |
| ERP Help others | 677 | 3.27 | 1.41 |
| ERP Optional events | 676 | 3.75 | 1.56 |

| | | | |
|---|---|---|---|
| Intention to leave | | | |
| Occasional | 1825 | 2.77 | 1.73 |
| In the next months | 1825 | 1.92 | 1.42 |
| In the next years | 1825 | 2.80 | 1.83 |
| Stay until retirement | 1825 | 5.07 | 1.16 |

Note: IRP = “In-role performance”; ERP = “Extra-role performance”.

The reported average productivity scores reveal that participants, on average, feel that they felt more productive for the types of tasks that are prescribed to them as part of their formal roles (i.e., in-role performance) (*M* = 13.94, *SD* = 2.83) than for optional tasks or engagements (i.e., extra-role performance) (*M* = 11.01, *SD* = 3.69). Regarding how soon participants believe that they might leave their current organisations, the data shows that the parameter with the highest score (indicating a stronger level of agreement with the statement) was the intention to stay long-term, perhaps until the retirement age (*M* = 5.07, *SD* = 1.16), which would seem to highlight that these participants likely feel that the organisation caters to their needs (which may be related to aforementioned higher positive than negative experiences).

Given the type of panel data being studied, and the aim of this research, the appropriate models must take into account the lack of independence of the standard error terms in the models used and that the dataset may be unbalanced, as is the case with the present study. To ensure that the correct model was used, Hausman tests were conducted (Wooldridge, 2010) to confirm whether the choice of a Random Effects (RE) model was appropriate over a Fixed Effects (FE) model. This process involves computing both FE and RE models fitted to the data to then run a confirmatory Hausman test that indicates whether the individual level effects are sufficiently captured by a FE model which assumes that they are constant; or whether these individual effects are random (following a normal distribution).

*6.2.1 Productivity as a result of positive affect*

Two Hausman tests were conducted (for regression of in-role and extra-role performance), and the results suggest that when the models are compared, a regression using a Random Effects (RE) model was the appropriate choice for both the in-role ($\chi^2$ = 0.35, $p$ = .553) and extra-role performance ($\chi^2$ = 0.80, $p$ = .372) models. The RE model estimated that the effect of positive affect on the variance of in-role performance is 40% for in-role productivity and 47.59% for extra-role performance.

The models estimated the effect of positive effect on in-role performance to be significant and positive, leading to an improvement of 0.22 points in the in-role performance perception ($z$ = 9.74, $p$ < .001). For extra-role productivity, the effect of positive affect is positive and significant ($z$ = 5.32, $p$ < .001) leading to 0.14 points improvement in the in-role productivity score.

Next, the effect of each positive affect scale on in-role and extra-role productivity was investigated. The mono-predictor models for in-role and extra-role performance showed that all individual positive affect scales were statistically significant predictors. The table below summarises the findings.

**Table 14**

*Regression table: positive affects as predictors of productivity.*

| | Content | Good | Happy | Joyful | Pleasant | Positive | Positive affect |
|---|---|---|---|---|---|---|---|
| **In-role productivity** | | | | | | | |
| N | 106 | 106 | 106 | 106 | 106 | 106 | 106 |
| N obs | 662 | 661 | 662 | 662 | 661 | 662 | 663 |
| Coeff. | 0.76** | 1.00** | 0.90** | 0.94** | 0.85** | 1.12** | 0.22** |
| Std Error | 0.11 | 0.13 | 0.12 | 0.11 | 0.11 | 0.13 | 0.02 |
| z | 6.62 | 7.65 | 7.49 | 8.75 | 7.44 | 8.52 | 9.74 |
| p-value | < .001 | < .001 | < .001 | < .001 | < .001 | < .001 | < 0.001 |
| Rho (%)* | 38.86% | 39.68% | 39.51% | 40.66% | 39.58% | 38.59% | 39.96% |
| **Extra-role productivity** | | | | | | | |
| N | 106 | 106 | 106 | 106 | 106 | 106 | 106 |
| N obs | 676 | 674 | 676 | 676 | 675 | 675 | 676 |
| Coeff. | 0.55** | 0.71** | 0.62** | 0.53** | 0.43** | 0.65** | 0.14** |
| Std Error | 0.13 | 0.15 | 0.13 | 0.13 | 0.13 | 0.15 | 0.03 |
| z | 4.35 | 4.76 | 4.56 | 4.14 | 3.34 | 4.30 | 5.32 |
| p-value | < .001 | < .001 | < .001 | < .001 | 0.001 | < .001 | < .001 |
| Rho (%)* | 47.18% | 48.43% | 49.03% | 47.27% | 47.52% | 47.62% | 47.59% |

* The percentage displayed is equivalent to rho which represents the ICC – intraclass correlation – or the amount of variance of the dependent variable in the regression that is explained by the independent variable group characteristics.

** Statistically significant at p = .001

These results show that positive affect scales strong predictors of both types of performance, with the in-role performance test statistics being particularly strong, and for extra-role performance, the positive affect scales individually explained a considerable percentage of the variance (all over 47.18%).

To determine how effective each individual affect was when controlling for the remaining positive emotions, as established in the SPANE model, a composite model was computed to include all scales of PA and assess whether the individual scales, controlled for separately rather than as a composite score (i.e., “positive affect score”) were statistically better predictors than the composite PA scores. These models showed that variance in extra-role performance was not appropriately predicted by a combination of the various positive emotions (none of the predictors were significant), while the in-role regression model showed that the scales "joyful" and "positive" were statistically significant positive predictors of the dependent variable. Feeling joyful was estimated to increase the in-role performance score by 0.53 points ($z$ = 3.06, $p$ = .002), and feeling positive by 0.50 points ($z$ = 2.29, $p$ = .022). This model accounted for 41.23% of in-role productivity variance, which is a slight improvement over the single predictor models.

*6.2.2 Productivity as a result of Negative affect*

Continuing the analysis into the effect of momentary affect experiences and their impact on productivity, two Hausman tests were conducted (for regression of in-role and extra-role performance), and the results suggest that when the models are compared, a regression using a Random Effects (RE) model is the appropriate choice for both the in-role ($\chi^2$ = 0.23, $p$ = .632) and extra-role performance ($\chi^2$ = 0.13, $p$ = .72) models. The RE model estimates that negative affect explains 40.19% of in-role productivity variation, and 49.29% extra-role performance. The models estimate the effect of negative effect on in-role performance to be significant and negative, leading to a decrease of 0.22 points in the in-role performance perception ($z$ = -6.75, $p$ < .001). For extra-role productivity, the effect of negative affect is not significant ($z$ = -0.46, $p$ = .649), providing preliminary partial support for H1a which predicted that PA would predict higher productivity scores than NA, however, this initial analysis was not able to confirm this to be the case for extra-role performance.

Next, the effect of each negative affect scale on in-role and extra-role productivity was analysed. The single predictor models for in-role and extra-role performance showed that all individual negative affect scales were statistically significant predictors. The table below summarises the findings. Hausman tests conducted for all models indicated that RE models were suitable for both in-role and extra-role models with the variables angry ($\chi^2$ = 0.71, *p* = .399 and $\chi^2$ = 0.01, *p* = .915, respectively), bad ($\chi^2$ = 0.00, *p* = .996 and $\chi^2$ = 0.02, *p* = .878, respectively), negative ($\chi^2$ = 0.02, *p* = .884 and $\chi^2$ = 1.22, *p* = .269, respectively), sad ($\chi^2$ = 0.00, *p* = .983 and $\chi^2$ = 0.00, *p* = .983, respectively), unpleasant ($\chi^2$ = 0.01, *p* = .942 and $\chi^2$ = 0.30, *p* = .586, respectively), except for the model using afraid as the predictor variable where in-role productivity required a FE ($\chi^2$ = 3.93, *p* = .047), and extra-role productivity was best suited for a RE model ($\chi^2$ = 0.37, *p* = .546), and tired as an independent variable where in-role performance was best estimated with a RE model ($\chi^2$ = 1.09, *p* = .297) and extra-role performance with a FE model ($\chi^2$ = 4.84, *p* = .023).

**Table 15**

*Regression table: negative affects as predictors of productivity.*

| | **Angry** | **Afraid** | **Bad** | **Negat.** | **Sad** | **Unpl.** | **Tired** | **Negat. affect** |
|---|---|---|---|---|---|---|---|---|
| **In-role productivity** | | | | | | | | |
| N | 106 | 106 | 106 | 106 | 106 | 106 | 94 | 106 |
| N obs | 662 | 662 | 663 | 662 | 662 | 662 | 534 | 662 |
| Coeff. | -0.75** | -0.57** | -0.88** | -0.90** | -0.67** | -0.78** | -0.32** | -0.22** |
| Std Error | 0.16 | 0.14 | 0.17 | 0.15 | 0.16 | 0.15 | 0.09 | 0.03 |
| z[1] or t[2] | -4.62(1) | -4.04(2) | -5.30(1) | -6.02(1) | -4.07(1) | -5.27(1) | -3.52(1) | -6.75(1) |
| p-value | < .001 | < .001 | < .001 | < .001 | < .001 | < .001 | < .001 | < .001 |
| Rho (%)* | 41.92 | 48.37 | 40.09 | 40.71 | 40.89 | 40.23 | 49.19 | 40.19 |
| **Extra-role productivity** | | | | | | | | |
| N | 106 | 106 | 106 | 106 | 106 | 106 | 106 | 106 |
| N obs | 676 | 676 | 676 | 675 | 675 | 676 | 676 | 676 |
| Coeff. | 0.32 | -0.13 | -0.15 | -0.09 | -0.24 | -0.06 | -0.11 | -0.02 |
| Std Error | 0.19 | 0.14 | 0.20 | 0.17 | 0.20 | 0.16 | 0.12 | 0.04 |
| Z(1) or t(2) | 1.65 | -0.93 | -0.77 | -0.51 | -1.16 | -0.39 | -0.98 | -0.46 |
| p-value | .099 | .351 | .438 | .611 | .244 | .693 | .325 | .649 |
| Rho (%)* | 49.42 | 49.25 | 49.32 | 48.87 | 49.33 | 49.33 | 52.87 | 49.29 |

* The percentage displayed is equivalent to rho which represents the ICC – intraclass correlation – or the amount of variance of the dependent variable in the regression that is explained by the independent variable group characteristics.

** Statistically significant at p = .001

These results show that negative affect scales are good predictors of in-role performance, but not of extra-role performance. The individual negative affect scales were all significant and negative predictors of in-role productivity, with coefficients ranging from -0.57 to -0.90 (afraid and negative, respectively), whereas none of these scales was shown to significantly predict changes in extra-role performance scores.

Following a review of how each individual NA scale predicted performance score changes, additionally complex models were computed to assess whether the combination of the individual negative affect scales as part of the same predictive model was a statistically better predictor than the composite NA scores (i.e., "negative affect score"). The results revealed that this was not a good model to explain variance for extra-role performance, for which the only significant predictor was experiencing anger, which showed a regression coefficient of 0.66 extra-role performance points ($z$ = 2.65, $p$ = .008). The in-role performance regression model showed that the scales "afraid" and "tired" were statistically significant predictors of the dependent variable. Feeling afraid or anxious was estimated to decrease the in-role performance score by 0.37 points ($z$ = -2.59, $p$ = .010), and feeling tired by 0.20 points ($z$ = -2.14, $p$ = .032). This model predicted 47.70% of in-role productivity variance.

With the NA regression models results analysed alongside with the PA results above, the analysis appeared to support H1a that suggested that positive affect would predict higher performance scores than negative affect, which seems to be the case for each individual scale, both for in-role and extra-role performance scores.

However, until this point, H1b (affect experiences are stronger predictors of extra-role than in-role performance) remains partially supported since the "PA score" and "NA score" explained a larger proportion of the extra-role variation than in-role, however, when the item-level scales are analysed combined as individual predictors rather than as an overall PA or NA score, the extra-role performance models were largely non-significant.

*6.2.3 Productivity as a result of Affect balance*

The final affect-related variable to be investigated as a predictor of productivity was affect balance. A Hausman test was conducted (for in-role and extra-role performance regression models), and the results suggest that when the models are compared, Random Effects (RE) models are the appropriate choice for both the in-role ($\chi^2$ = 0.45, $p$ = .505) and extra-role performance ($\chi^2$ = 0.43, $p$ = .51). The RE model estimates that the effect of affect balance on in-role productivity is responsible for 39.71%, and 48.41% for extra-role performance. The effect on in-role performance score is strong, significant and is expected to increase it by 0.15 points for each 1-point increase in affect balance score ($z$ = 9.92, $p$ < .001). With regards to extra-role performance, the effect of affect balance is also significant, with a predicted improvement in the performance score of 0.07 ($z$ = 3.88, $p$ < .001).

Two final models were computed with the two types of productivity as the dependent variable: one with in-role productivity, one with extra-role productivity. The independent variables were all the positive and negative individual scales, for a total of thirteen predictors. Hausman tests confirmed that RE models were appropriate ($\chi^2$ = 15.59, $p$ = .272 for in-role, and $\chi^2$ = 10.1, $p$ = .686 for extra-role productivity). The results indicated that in-role productivity was significantly improved for those with higher scores of joyfulness (coeff. = 0.73, $z$ = 4.19, $p$ < .001) and significantly lower for those with higher scores of fear/anxiety (coeff. = -0.31, $z$ = -2.26, $p$ = .024). This model explains 49.13% of the in-role performance score variance. With regards to extra-role productivity, being angry was the only significant predictor (coeff. = 0.67, $z$ = 2.76, $p$ = .006) and the ability to explain 53.35% of the extra-role productivity score variance.

These findings further supported the hypothesis that affective experience would be most suitable to explain extra-role performance (H1b), with this affect balance composite model explaining a slightly improved proportion of the performance variance.

*6.2.4 Productivity as a result of work tasks*

Two Hausman tests were conducted (for regression of in-role and extra-role performance), and the results suggest that when the models are compared, a regression using a Random Effects (RE) model is the appropriate choice for both the in-role ($\chi^2$ = 5.27, *p* = .384) and extra-role performance ($\chi^2$ = 2.05, *p* = .842) models. The RE model estimates that the effect of positive affect on in-role productivity is responsible for 42.75%, and 50.42% for extra-role performance.

The first model estimated the effect of performing different categories of tasks at work on in-role performance to be significant, strong, and positive, leading to an improvement of 2.52 points in the in-role performance perception (*z* = 2.88, *p* = .004). Since the descriptive statistics identified procrastination as the task that scored lowest, on average, for positive affect which has been shown to be a good predictor of productivity (see analysis above), a model was estimated where this was the base variable whereby its coefficient is omitted as the base variable (i.e., “not present while”, or zero) computing the remaining coefficients (i.e., in categorical variables participants either “are” or “are not” in each category; if one is “not” procrastinating, then the remaining categories may be estimated, as being true). The model estimated the regression coefficients for the remaining five categories of work tasks: “taking a break”, “performing a usual task”, “performing an unusual task”, “being in a meeting”, and “being on a call”. The model reveals that all but “taking a break” are significant predictors of in-role productivity, with noticeable improvements in the performance score (of up to 20%). The effects on in-role productivity predicted by “performing a usual task” (*z* = 5.40, *p* < .001) reveals an improvement of 2.69 points in the performance score (14.94% improvement); “being in a meeting” (*z* = 4.63, *p* < .001) and which increases the in-role productivity score by 2.76 points (15.33% score increase); “being on a call” (*z* = 3.97, *p* < .001) leads to an increase of in-role productivity scores of 3.63 points (20.17% improvement); finally, “performing an unusual task" was also a significant and positive predictor of in-role productivity ($z$ = 4.05, $p$ < .001), contributing to a score increase of 2.21 points (12.28%).

For extra-role productivity, the effect of work tasks is not significant ($z$ = 0.81, $p$ = .416), however, it is relevant to investigate whether any of the individual categories of tasks might be an adequate predictor which could possibly be concealed in the broad category results. This resulted in a model that highlighted three of six task categories which predicted significant changes in extra-role productivity, albeit smaller and not as strong as those seen for in-role performance scores. The effect of "being in a meeting" ($z$ = 2.33, $p$ = .020), "performing an unusual task" ($z$ = 2.20, $p$ = .028), and "performing a usual task" ($z$ = 1.97, $p$ = .048), were seen to have a significant and positive impact on the extra-role productivity scores, improving it by 1.55, 1.28, and 1.07 points (respectively). These improvements range from 5.94% to 8.61% in extra-role performance. Taking breaks and procrastinating, unsurprisingly, were not significant predictors of either type of productivity which is likely due to these tasks, by nature, revolving specifically around not performing any work endeavours – in one case intentionally and with other known benefits (e.g., taking a break – resting), and in another case often unintentionally and with other known downsides (e.g., procrastinating – feelings of guilt) (Finkbeiner et al., 2016).

Hypotheses H2a and H2b (2a: in-role performance is likely to be predicted by tasks that directly relate to the performance of one's job; 2b: work-related tasks are likely to be better predictors of in-role than extra-role performance) are both supported by these results. The first could be seen to be supported particularly by the fact that "taking a break" was the one category of work tasks that did not show a significant effect on in-role productivity, whereas for extra-role productivity the effects were smaller and fewer. The second hypothesis was confirmed by the demonstration of in-role performance scores being improved to a higher degree than extra-role performance scores.

*6.2.5 Productivity as a result of social interactions*

Continuing the analysis to explore whether time varying factors related to context are relevant and significant predictors of productivity, two Hausman tests were conducted (for regression of in-role and extra-role performance), and the results suggest that when the models are compared, a regression using a Random Effects (RE) model is the appropriate choice for both the in-role ($\chi^2$ = 1.41, *p* = .234) and extra-role performance ($\chi^2$ = 0.80, *p* = .372) models. The RE model estimates that the effect of positive affect on in-role productivity is responsible for 40.15%, and 49.05% for extra-role performance.

The first model estimated the effect of interacting with different categories of people at work on in-role performance to be significant and positive, leading to an improvement of 0.16 points in the in-role performance perception (*z* = 2.29, *p* = .022) as opposed to not interacting with others. Since the general model does not provide sufficiently interesting information, a new model was estimated where regression coefficients are computed for the categories of workplace interactions: "no interactions / alone" was used as the base category for the models; the remaining categories for which coefficients were calculated were "interacting with only personally related others" (e.g., partner, friends), "interacting with only professionally related others" (e.g., manager, client), "interacting with a mix of personal or professional relationships" (e.g., partner and co-workers). The model reveals that effects on in-role productivity are only significantly predicted by interacting with professional connections only (*z* = 2.40, *p* = .017), which improves the in-role performance scores by 0.52 points.

For extra-role productivity, the effect of social interactions is significant (*z* = 3.98, *p* < .001), and increases the score by 0.30 points. To further investigate which individual categories of interactions are the strongest predictors of extra role productivity, another model was fitted – similar to the process described above. This resulted in a model that revealed two significant extra-role productivity predictors, with larger effects than those seen for in-role productivity (mentioned above), which is in line with the third hypothesis of this study. The effect of interacting with a combination of people who may be related to both the individual's personal and professional spheres was significant ($z$ = 2.77, $p$ = .006), as were the interactions with only work-related parties ($z$ = 4.07, $p$ < .001), each improving the extra-role productivity score by 2.34 and 0.94 points (respectively, which is a range of improvement of 5.22% to 13%).

### *6.3 Discussion*

This study's aims were to investigate whether time varying variables measured through ESM were adequate predictors of productivity, to advance the conversation in the literature that generally indicates that well-being is an antecedent of occupational outcomes such as productivity (Diener et al., 2018) (H1a and H1b), as well as effect of context (H2a, H2b and H3a) on performing one's role. This was done by analysing the impact of the subjective well-being affective component, categories of work tasks, and categories of workplace social interaction on in-role and extra-role performance assessed via momentary self-reports on both productivity scales.

The findings suggest that the first hypothesis, stating that affective experience predicts productivity, was supported and is in line with recent research showing similar results (Bellet et al., 2019) albeit not using momentary ESM methodologies. As part of this hypothesis, it was anticipated that positive affect would predict better performance than negative, which was also supported. However, it is worth noting that when analysing the most inclusive model, where all positive and negative affect variables were included in the explanatory model, extra-role performance scores were improved by demonstrating higher levels of anger, which was surprising. And while the result was non-significant, those with higher "feeling bad" ratings also showed a tendency towards higher self-reported performance scores (coeff. = 0.16, $z$ = 0.46, $p$ = .64), while all other negative affect scales, as expected, showed a tendency to lower performance scores. There are two ways to potentially explain these surprising results. Firstly, there is a possibility that due experiencing higher levels or anger, individuals might have shifted their focus from in-role performance (prescribed and formal tasks associated with their roles, where “anger” indeed contributed to a worsening of performance scores), to extra-role tasks which are optional, and perhaps more social in nature, to appease their anger at the moment of ESM data collection. Secondly, the individual’s perception that they are performing well at the extra-role level could be partly related to them feeling angrier if, perhaps, they did not feel recognised or rewarded for their non-mandatory efforts. With the present study design, it is not possible to distinguish between these two scenarios.

Another key finding from this study is that it appeared to indicate that experiencing higher levels of negative affect at work would have the biggest impact on core responsibilities and tasks – those are that are central to one’s role – rather than on tasks that are optional and/or secondary to the overall team and organisation performance. This was seen through the higher coefficients for the in-role rather than extra-role performance regression models. Notwithstanding, the models computed and analysed were consistently better at predicting the variance of extra-role performance scores, i.e., a larger proportion of variance of extra-role performance appeared to be caused by the participants’ affective experiences. This finding is in line with previous literature (Tenney et al., 2016; Oswald et al., 2015) that suggested that SWB measures could be best suited to explain extra-role performance. In summary, the findings from this study aligned with a large proportion of past cross-sectional research, even though a recent 2017 study by Bryson et al. showed no significant relationships between SWB and productivity at work, however, productivity measures were mostly at the organisational level (i.e., finance and accounting indicators were most used) rather than at the individual level where one might expect the largest impact of individual affective experience to be, as well as using job-related anxiety as the main affect based measure of workplace affective experiences.

This study’s results also showed that, as predicted in hypothesis two (2a and 2b), work-related tasks were better predictors of in-role than extra-role performance.

Importantly, the results confirmed that when performing work-related tasks, the in-role performance scores, i.e., self-reported perception, were up to 20% higher than when procrastinating. This is in line with suggestions that improving attentional focus on work tasks correlates to higher productivity (Toniolo-Barrios & Pitt, 2021; Lai et al., 2020).

An interesting and note-worthy finding stemming from the present study was the fact that extra-role productivity was better predicted by social interactions than in-role productivity, fully supporting the third hypothesis of this study. While this finding appears to align with existing literature that suggests that extremely happy individuals tend to do very well in social relationships (Oishi et al., 2007), and Cai et al.'s (2014) finding that informal relationships have an impact on performance, but not formal ones, it is not entirely clear what the specific link between relationships in the workplace and productivity is, and more research is needed in this topic before making definitive claims. Park et al. (2004) suggests that there is a relationship between social support at work and performance, however, social support is a different metric than the one utilised in the present study. Results must be considered cautiously.

This study includes some limitations. Firstly, the granularity of the categories within work tasks and social interactions at work might be too general and fail to acknowledge a deeper level of distinction between everyday situations, as was mentioned in study two. Secondly, this study included self-reported measures of performance, but not objective indicators. This might lead to results that could be distorted based on individual perceptions, particularly with the knowledge that people who experience more negative affect or negative mental health, it could lead to the individuals reporting lower levels of performance for themselves (Shi et al., 2013; Foo et al., 2009). Future ESM studies looking to investigate the connection between the outcome of individual productivity and how people feel, act, and interact with others at work should consider objective measures in addition to self-reports, as well as distinguish between those who might have known mental health issues with the potential to affect such type of measures – to name just two of the most researched conditions, anxiety and depression. Thirdly, the data collection for this study occurred before the COVID-19 pandemic. The world of work has since shifted and adjusted, and might not return to where it was once, as it was. Due to the circumstances at the time of designing this intervention, this study presumed that most participants who were employed, would have worked from a stipulated physical location as set out in their employment agreements. If the last two years have been any indication, this should lead to future research that expands on these findings while incorporating the much more diverse contextual elements that are true of 2023 (and onwards) workplaces. While the use of technology was already present before the pandemic, it could be argued that their impact and/or inclusion in an employee's considerations of their workday would have been minimal, and as such it did not invoke a great deal of thought upon planning this study. This is no longer the case and is likely to remain a branch of everyday work life that would not be expected to revert to where it was pre-pandemic.

### *6.4 Conclusion*

This study's intention was to further the well-being research by using an ESM methodology to confirm the suitability of generating performance perception predictions based on momentary affective experiences. Further, using the ESM methodology, the study also sought to verify whether other time varying antecedents could be confirmed for productivity, namely with the assumption that the types of tasks being performed, and the people with whom employees interact will impact their productivity.

It was found that, firstly, the use of time varying variables is suitable to investigate the relationship of different factors and an important occupational outcome – productivity, in the form of self-reported in-role and extra-role performance. It cautiously confirmed that affective experience, work tasks, and social interactions at work are significant and relevant predictors of productivity. Affective experience is a good predictor of productivity, particularly via positive affect. Similarly, it was found that work-related tasks were better predictors of in-role than extra-role performance, and social interactions at work were better predictors of extra-role performance.

These results are encouraging and contribute to the literature in novel ways: they added knowledge to the debate of whether and how real-time experiences of employees relates to productivity, via how they feel, what they do, and who they interacted with.

## Chapter 7: Overall Discussion

This thesis set out to fulfil two main goals. Firstly, to investigate the relationship between the affective component of subjective well-being (positive and negative affect) and individual differences, situational characteristics, and workplace productivity. Throughout the discussion, the word "happiness" will be used to refer broadly to the affective experiences that were measured in the three studies conducted and reported in the previous chapters. By looking at happiness as an outcome of individual differences and situational aspects, place happiness in a position of being a consequence of variables both within and outside of the individuals' control. By looking at happiness as the source of workplace performance and productivity, it lends happiness this dualistic perspective as it is also considered as the antecedent of occupational outcomes.

Secondly, this thesis aimed to implement a novel methodology of experience sampling for the study of happiness, by developing a mobile application for this purpose. ESM is a methodology to collect momentary happiness responses, in real-time, alongside information pertaining to the participants current context. ESM may be applicable outside of the context of work; however, the focus of this thesis was workplace environments and contexts and as such this discussion will primarily consider this setting. The intention of developing a mobile app for the purpose of conducting an ESM study was twofold. First, the aim was to determine whether this methodology is a suitable mechanism to investigate the relationship between happiness and its proposed antecedents (individual differences, personality, working activities, social interactions at work) and outcomes (in-role and extra-role performance).

This thesis included three studies. In the first study momentary perceptions of affective experiences were measured over multiple time points (longitudinal continuous outcomes, variable over time), while individual characteristics data was collected only at the beginning of the study, since this data is not expected to change over time as these are relatively stable variables with temporal stability. The study investigated the relationship between personality and other individual differences with happiness. In this study, happiness is a consequence of variables that are outside of the participants' control. A prime objective of Study 1 was to identify to what extent temporally stable variables predict happiness, the outcome variable that is malleable and changes both within person and through time. The study produced mixed findings. Firstly, none of the demographic variables investigated was a significant predictor of both positive and negative affect; it was seen that age and education predict positive affect, whereas employment type (i.e., being self-employed) explained negative affect differences, and age and experience predicted the balance score. Secondly, personality traits (broad and narrow) predicted all types of affect when using the traits independently of one another, but when combined into a model that reflects each personality framework only one broad trait (conscientiousness) and one narrow trait (vision) showed predictive significance in the model. Thirdly, when multiple demographic variables and/or personality traits were combined in the same regression model, the results indicated that few of the variables retained their relevance as predictors of happiness and the more complex models do not explain a larger proportion of variance in the dependent variable. This is likely caused by the independent variables sharing unknown or unmeasurable variance (for example, younger individuals can be reasonably expected to have fewer years of working experience). Fourthly, the degree of score change predicted by each personality trait (regressed individually) was very small; the scores themselves only improve by a small proportion, and the models only estimate around 30% of the variance in happiness. There had been concerns raised in the literature that despite the overwhelming and broadly accepted view that personality and demographic variables are good predictors of happiness, they may not have the sufficient flexibility needed to explain SWB more fully (Friedman & Kern 2014; Sonnentag, 2015). Study 1 revealed that these temporally stable independent variables were only able to predict a smaller proportion of real-time happiness scores than would have been expected from past studies. This is cause to consider the implementation of more novel approaches such as ESM, but also to measure SWB beyond its cognitive component of satisfaction with life, which has been the gold standard in SWB research (e.g., Pavot, 2018). A recent study (Killingsworth, 2021) revealed contradictory empirical evidence regarding the association between income and happiness primarily by using a more robust methodological approach than the original study conducted by Kahneman & Deaton (2010). The original study had claimed that income was only associated to increased SWB for incomes up to $75,000, however it had severe methodological impairments. In the 2010 cross-sectional study, SWB was measured on a dichotomous scale (yes/no). By implementing an ESM (despite the data having been aggregated into an average score per individual) and using a continuous scale to assess SWB, Killingsworth (2021), was able to demonstrate that in fact happiness continues to increase with income. While understanding and acknowledging the importance of this evaluative perspective, it appears short-sighted to continue to deny the relevance of individuals' experiences as well as the strengths of more modern methodological approaches. While it has been suggested before that since the experiences are relatively short-lived (Pavot, 2018) as a way to justify the much less developed stream of research that focuses on the temporally unstable affective component of SWB, we must acknowledge its relevance in many ways. For example, in the context of someone's life, and assuming mostly average occurrences (i.e., no drastic changes, positive or negative – the individual does not win the lottery, but they are also not the victim of an extraordinary tragedy), it is not surprising that SWB measured as satisfaction with life might remain relatively stable. There would be no reason to think otherwise. If we were to measure this individual's satisfaction yearly for several years, we might eventually identify dips and peaks, and a return to an average value. This speaks to the limitations of averaging observations even when dealing with the more stable component of SWB. However, assuming that this individual's life satisfaction is approximately the same throughout the course of their life, it is still of interest to understand the SWB changes that may precede or succeeds important decisions that largely affect one's life. For example, the impact on and from SWB through experiences such as deciding to change jobs, moving to a new city, or starting a family. In the context of occupational psychology, there is very realistic need to have a better understanding of individuals' affective experiences in many different contexts. Not only so that occupational psychologists to fulfil their broad role of helping organisations succeed while catering for employee's needs, but to ensure that the organisation is equipped to deal with different types of needs at different moments and stages. Recent statistics have shown that in the UK alone, in 2018, over 17.5 million days of work were lost due to poor mental health; in 2020-2021 there was a 25% increase of employer cost regarding mental health caused by absenteeism, presenteeism, and turnover when compared to 2019, for a total of £53-56 billion, or approximately 2.6% of the country's Gross Domestic Product (Deloitte, 2022). The office for national statistics (ONS) published their Labour Force Survey results (see: Sickness absence in the UK labour market 2022), which suggests that mental health has been the cause for approximately 14% of from work. The costs that organisations incur related to productivity loss in general, and time lost for mental health reasons in particular is so great that employers would benefit from a deeper understanding of what the realistic experiences that affect their workforces are – positive or negatively.

Study 2 further contributes to the understanding of how work specific situational aspects affect happiness at work. The study placed happiness as the outcome of situational variables work activities and social interactions at work. The results showed that situational and social interaction predictors were stronger than the individual difference predictors seen in study 1. They explained both a larger proportion of variation (of 48-53% throughout) and their predicted impact on the affective experience scores was larger. Interestingly, when participants reported to be "procrastinating", it was not shown to significantly impact happiness (positive, negative or balance scores). Since this was the only activity category that essentially and specific precludes the actual performance of a pro-work behaviour, it could help understand the reason behind the non-significant impact of engaging in what is often seen as potentially harmful behaviour. However, since one of the limitations of study 2 was the disregard for the length of each behaviour, it is plausible that perhaps the procrastinating behaviour was not engaged in for a sufficiently long duration to impact the affective experience that the employees report during their working periods. Alternatively, it could also simply be a relatively neutral way to use a portion of time during the workday. This was a distinctive behaviour from “taking a break” from work, as both options were available. Taking a break was seen to predict positive affective experiences, which suggests that it may be related to the process of recovery that has been proposed relates to task performance (Finkbeiner et al., 2016). This study also found that being alone was the social interaction situation that produced the lowest level of positive affect while at work, a finding that aligns with a recent study by D’Oliveira & Persico (2023) who found that isolation at work can harmful and produce adverse impacts. The presence of some form of social interaction in the workplace is likely to foster feelings of support, which has been shown to be related to higher levels of job satisfaction (Bakker, 2011; Simbula, 2010), feelings of self-efficacy (Xanthopoulou et al., 2008), and humour which is shared with the others (Xanthopoulou et al., 2012), suggesting that there are a variety of mechanisms through which the interactions with others at work would contribute to better affective experiences. Since this study’s data collection occurred before the COVID-19 pandemic, the assumption is that the majority of the interactions reported by participants would have happened face-to-face, rather than virtually. This would constitute an interesting further research point to determine whether there are differences, and if so how do they translate into positive and/or negative affect experiences, depending on whether the workplace activities and interactions that study 2 investigated were to take place in a shared physical environment, such as an office, versus a virtual environment. An interesting future research path would involve researching the suitability of methodologies that generate real-time data to investigate meaningful correlations between SWB and other well-established occupational psychology theories. For example, engagement has been associated to SWB at work (Bakker, Hakanen, et al., 2007), the work tasks themselves (Christensen et al., 2020; Christian et al., 2011), as well as the social aspects of the workplace (Decuypere & Schaufeli, 2020). Saef et al. (2021) suggest that empirical evidence supports the notion of a distinct relationship between job demands and engagement depending on whether it is approached from a perspective of differences between people (the higher the job demands, the lower the engagement), versus differences within people measured with momentary methodologies (higher job demands are linked to higher engagement) (Bakker, Van Emmerik, et al. 2007). It is worth nothing that while engagement is quite often used interchangeably with SWB, there is empirical evidence to suggest that they are not the same construct (Joo & Lee, 2017).

These findings stemming from the engagement literature are well aligned with the results seen in Study 3 which clearly showed that momentary happiness is a suitable predictor for momentary perceptions of productivity. While the engagement literature is very broad and slightly unfocused, the general agreement is that highly engaged employees tend to be productive (Bakker, Hakanen, et al., 2007). Engagement has also been shown to relate to positive affect (Christensen et al., 2020), which would suggest that there may be a moderation or mediation relationship whereby workplace engagement might affect, or explain, the relationship between happiness at work and productivity.

This study presented a surprising outcome. Analysing the relationship between happiness and productivity, the expectation had been that higher positive affect would contribute to better performance, while higher negative affect would have reduced or worsened performance (Bellet et al., 2019). However, the results showed that there was a significant positive impact on performance predicted by feeling angry.

The data itself does not offer a good reason for this to be the case, which calls for some speculation. Firstly, it further highlights that this major gap in theoretical frameworks and empirical evidence as it pertains to momentary experiences of SWB and its effect on occupational outcomes still requires some investigation. Secondly, this finding might be related to activation levels rather than the polarity of the feeling. As mentioned above regarding engagement, the fact that an employee reveals engagement at work tends to be associated with higher levels of SWB, however, it is also associated with higher activation (Reijseger et al., 2017). The fact that one might feel higher levels of anger at one given point, could translate into affective activation which could then lead to productivity gains. It is important to note that that this might not have been true if the levels of anger might have been so high that the individual struggled to manage their own emotions, since emotional regulation have also been associated to better work performance by refocusing an individual's attention to pressing matters or topics that require improvement immediately (George & Zhou, 2002).

The findings presented in study 3 also revealed that the momentary happiness and work-related factors were better predictors of extra-role performance than in-role performance, which aligns with previous findings (Tenney et al., 2016; Oswald et al., 2015). However, this finding calls for further investigation given the limitations of the present study. One of such limitations might be the short form of the self-assessed performance measures, and the fact that they were self-assessments in the first place. A future improvement to further clarify these findings would potentially lead to conducting a study where objective individual performance measures are obtained and cross-referenced with the self-reported affective experience and the self-reported performance. One of the primary reasons why this might pose challenges is, naturally, the matter of confidentiality and access to sensitive personal information. That fact alone might lead to participants opting out due to concerns for their privacy, and that being the case, it raises another important point that has not received enough attention in occupational psychology studies – would that indicate a systematic pattern of those who elect not to participate? That might already be the case with the many studies conducted in the field of psychology where participation is both optional and voluntary. There is no way to know for sure whether those who self-exclude do so due to a systematic reason. For example, it is possible that those who self-exclude from a SWB study might be systematically less happy than average, potentially not wanting to reveal (even if anonymously) the lower happiness levels (perceived or actual).

Another limitation that is worthy of note regarding the studies conducted as part of this project and may have contributed to the results reported throughout is the fact that the workplace activities and social interaction categories might not have been granular enough to enable this study to find other meaningful results. For example, given that in-role performance relates to the performance of tasks that are intrinsically and explicitly related to a person's role, they are prescribed, known to both the individual and management, and form the bulk of one's workday, it could be argued that the six categories available to participants in this study were not specific or distinctive enough to produce different results. Indeed, the general categories were produced intentionally as this study aimed to recruit participants from multiple countries, companies, and industries. One of the downsides was the lack of ability to pre-determine what might have been suitably granular alternative categories. In short, if this study had aimed to investigate a similar hypothesis but regarding only "teachers in the UK", the instrument might have included specific tasks that are meaningful to the profession and that could offer a clearer and more interesting deep view into the workdays of participants. As it was, due to the nature and design of the study, the categories included general categories: "taking a break"; "procrastinating"; "in a meeting"; "on a call"; "performing a usual task"; "performing an unusual task". It is likely that this design and methodological limitation might have ultimately narrowed the response options so much that it reduced the richness of data artificially.

Future studies would be welcome to further develop the application of ESM methodologies in different workplace scenarios, including in occupational contexts that allow for the use of intervention versus control groups. This would contribute to the understanding of whether certain interventions, policies, or measures that the employer introduces have the desired effect, as well as measure the effect's duration accurately. In past research, using test-retest style approaches, a study might be able to determine if an intervention has produced an effect immediately after, and then at progressively larger time gaps afterwards (e.g., three months later, one year later, etc.). However, when the follow-up measurement is taken so sparsely, there is no way to tell how long the effect lasted, and to what extent. ESM methodologies might be helpful to address these gaps in knowledge and effectively bring practitioners' meaningful change that can be implemented within their organisations.

This study also introduced extensive strengths to the study of SWB, and this thesis contributions will be discussed next.

### *7.1 Thesis contributions*

The work developed as part of this thesis benefitted from a deeply rooted interest in contributing to the development of applied knowledge in the field of positive occupational psychology, by embedding the naturalistic elements of everyday life into the research design, rather than attempt to reason about them artificially, *a posteriori*. The knowledge produced here certainly bears the potential for important theoretical advancements, for example, by contributing to the encouragement of a more holistic approach towards how the experiences that individuals go through affects their experienced affect, and therefore their SWB, beyond the impact of infrequent and/or life altering events. However, the initial goal and intention has always been to offer a key methodological contribution to the field, which has consistently been singled out as lagging behind theory development. This goal has been achieved through the studies presented above.

Firstly, the experience sampling mobile app was entirely developed for the purpose of this research, which allowed for many useful customisations, several of which stemmed from a place of deeply considering ethical challenges and considerations, and minimising burden and other risks to the participant by understanding that research into the affective component of subjective well-being should be mindful, precisely, of the uniqueness and subjective nature of the experiences that participants bring to the field. These customisations included some straightforward aspects, such as which measures (i.e., surveys) to include, but also some logistics or user management aspects. For example, it was possible to establish cut-off periods for “silent times” during which the application would not bother participants. These were defined by the user by selecting the hours of the day that they would normally expect they could be reached. Users were given a suggestion that these could be their standard “being awake” daily periods but the researcher had no control over these choices. Users were also able to fine-tune how frequently they were willing to be prompted weekly, from a minimum of three times per week, up to seven days weekly. Most of the users selected somewhere between three and five days per week. Another critical ethical consideration was the access to personal identifiable data. The studies in this thesis and the ESM mobile application were designed with the intention of being fully anonymous from the beginning. As such, that allowed the application to be programmed such that no information that could constitute personal identifiable data was collected at any stage (e.g., no use of emails, I.P. addresses, device information, or even country of access). To reduce participant burden, two steps were taken. One pre-emptive decision was to limit the duration of each “session”. A session occurred each time that a participant opened the application in their smartphone to answer the study’s prompts. Since each session should take only a few seconds, a time cap of 120 seconds was set. If the participant was in the process of submitting a response, the data would come through, however, if the participant happened to be interrupted (for example, due to being at work) and was not able to complete the prompts, they would be allowed to complete the set displayed on screen, and then thanked for their input until next time. Another step was to pause all notifications (i.e., experience sampling prompts) if the user did not open the app for five consecutive days. The reasoning being that it could indicate disengagement or the intention to stop their participation, and therefore no additional burden would be placed on them. If a user chose to return to the app at a later date, the notifications would resume.

Secondly, by collecting longitudinal data at multiple times of the day and subsequently analysing said data without resorting to aggregating the data points into a mean value is a significant and important departure from previous research developed in the field, which has been increasingly noted as an important gap (Diener et al., 2018; Oswald et al., 2015; Sonnentag, 2015). That has required the researcher to investigate and incorporate methodologies which are traditionally most commonly used in medical research where this type of analysis of longitudinal non-aggregate data is employed. This methodological contribution should not be understated. While there were certainly weaknesses in the studies conducted, which deserve further research in the future, the methodological approach followed here provided an avenue to explore not only whether subjective well-being affective experiences can be predicted by the situation one is in – for example, being at work, or resting, or on holiday –, but critically and interestingly researchers can also determine whether the real-world and real-time changes and fluctuations that an individual feels on their subjective well-being affective experiences can be predicted by the varying situations that the person finds themselves is in.

In short, the work reported in this thesis demonstrates that transient affective states, i.e., momentary, real-time data regarding the affective component of subjective well-being is a productive and important addition or alternative to traditional cross-sectional studies or other modern ESM studies that work with aggregate data. The studies described in this thesis successfully addressed the methodological and theoretical gaps in the study of SWB that were set out in the initial chapters and offers a range of practical implications to occupational psychologists within the field of SWB. The overall contributions can be grouped as follows:

1. Demographic variables as predictors of momentary happiness are useful but provide an incomplete picture.
2. Personality traits as predictors of happiness offer useful but limited information.
3. Using work tasks to boost momentary happiness is a pathway worth further exploring, potentially by adding more granularity to the investigation of future longitudinal subjective well-being studies.
4. Using social interactions to boost momentary happiness is a pathway worth exploring to uncover additional details regarding the mechanisms that help explain the benefit of positive relationships at work, as well as the extent of the effect of those relationships that are not positive in nature.
5. Using momentary happiness to boost productivity perceptions could be an interesting avenue as participants self-reported productivity perceptions were show to relate to their affective experience in that moment.

The research presented in the thesis is not without limitations, which should encourage further investigations into these topics. For example, in this work, it was hypothesised that contextual and social features of our everyday lives would be suitable predictors of how one feels while those circumstances are ongoing. This was confirmed by the empirical data provided in earlier sections. However, this thesis did not delve into the length or intensity of these scenarios, nor did it add sufficient granularity to allow precise differentiation between similar situations that may bear different impact on the individual reporting on their transient affective experiences. Through the design of the studies in this manuscript, another potentially important development that was out of scope was the possibility (not tested here) of using this knowledge (i.e., that situations and social characteristics of a moment can help us predict the transient affective experience being felt) to experimentally test whether by manipulating the conditions that a person is in we could produce desirable improvements to their affective experience and therefore improve their SWB.

## Chapter 8: Conclusion

The study of happiness has long captivated scientists along with philosophers. The field has gained additional prominence in recent years as a result of greater awareness regarding the importance of mental health, and a concerted effort to frame human development not just as the absence of illness or maladaptive behaviours, but also as the presence of well-being and positive traits on their own.

As the field progresses, methodologies have not necessarily kept up quickly enough to match the ever-changing realistic needs and expectations of those for whom scientific progress is for: scientists and practitioners alike, as well as those who benefit from the new knowledge and the changes it brings, such as employers and employees who benefit from occupational psychology knowledge.

This thesis set out to fulfil two main goals. The first was to research the relationship between the affective component of subjective well-being (positive and negative affect) and individual differences, situational characteristics, and workplace productivity with the intention to further clarify how situational aspects help explain the variations in happiness reported by individuals. The second was the development and implementation of a novel methodology of experience sampling for the study of happiness, by creating a mobile app for this purpose, simultaneously demonstrating that the way in which happiness is measured, and the ways in which scientists may reach their participants technology that is becoming increasingly commonplace, with billions of smartphone sales each year (Mongardini & Radzikowski, 2020), is also evolving.

The studies reported here build on the knowledge from cross-sectional and longitudinal aggregates studies by researching a new layer of happiness – the impact of time as a variable. By adding this new layer, it was possible to examine the importance of individual differences, contextual, and social variables as antecedents of happiness, as well as explore how perceptions of productivity fluctuate over time in relation to the context and variations in happiness as an antecedent as well as contextual factors. The findings support that contextual and social variables are stronger predictors of momentary happiness fluctuations than stable variables (e.g., personality traits), as well as that there is scope for happiness as well as contextual workplace variables to be monitored and managed with the aim to improve both SWB in the workplace, as well as productivity. These results open the door for additional research that focuses on additional contextual factors to be investigated, as well as other antecedents of both momentary happiness and workplace productivity.

## Chapter 9: Recommendations

This thesis has presented empirical evidence that suggests that the recourse and implementation of modern, real-time, data collection methodologies brings advantages and adds to the knowledge in the field of positive organisational psychology, especially if and when combined with statistical analysis that does not require the researchers to sacrifice data richness by averaging responses into a single mean value per participant, and instead delves into the complexity of the fluctuations associated with the affect experiences that individuals go through daily.

When looking at wide-reaching statistical data, such as for example the UK's Measuring National Well-being programme first initiated in 2010 (Matheson, 2011), or OECD's Better Life Index (Index O.B.L., OECD, 2012), this data is critically important and informative as it paints a broad picture of how a society or country is doing based on a number of objective indicators (e.g., income, housing, etc.). However, it does not advance the conversation sufficiently when trying to understand what about our everyday lives produces positive and negative affect, and whether those experiences translate into meaningful differences between and within individuals. The latter can then be applied to realistic scenarios and aid in creating the conditions for individuals to flourish and live fulfilled lives. This helps us acknowledge that different people may have different needs, or priorities, and therefore understanding the subjective experiences brings a layer of analysis that was previously absent.

To continue to develop our theoretical and methodological understanding of the field of SWB at work, future efforts should be placed on gathering data that would enable the researchers to consider the length and intensity of the affective episodes in relation to length and intensity of the contextual factors that surround the individuals. This would then make it possible to further understand the extent to which these frequent affect fluctuations as demonstrated in the present work produce long-lasting effects on a person's life. It would also open the door to the understanding of the ways in which more or less frequent changes in one's affective life experiences can be associated to differing levels of the more stable and cognitive appraisals that a person creates of their own lives, or whether these would still remain better explained by the more stable objective indicators that past research has primarily relied on.

An interesting and exciting research avenue for the future to add to these findings is a continuation of improving the methodological advancements tested here by including novel ways to collect objective data and examine their relation to the subjective transient affective experiences. For example, research could focus on the use of wearable technology (e.g., smart watches, or monitoring systems) to further detect the impact of one's surroundings (e.g., noise levels, activity levels, social settings, etc.) or a person's internal objective indicators (e.g., heart rate, breathing rate, cortisol levels, etc.) to bridge the informational gap with the subjective indicators based on self-reports.

The findings of this thesis enable organisations to consider how the environment and contextual queues that they provide impact employees' experiences and affective SWB, which may in turn be used to produce recommendations or develop interventions which aim to reduce strain and negative affective experiences, whilst enabiling employees to feel increased positive affect. Ultimately, this is extremely useful from a point of view of job crafting as it allows both individuals and companies to devise ways that they see to be more conducive to flow states and ultimately of human flourishing.

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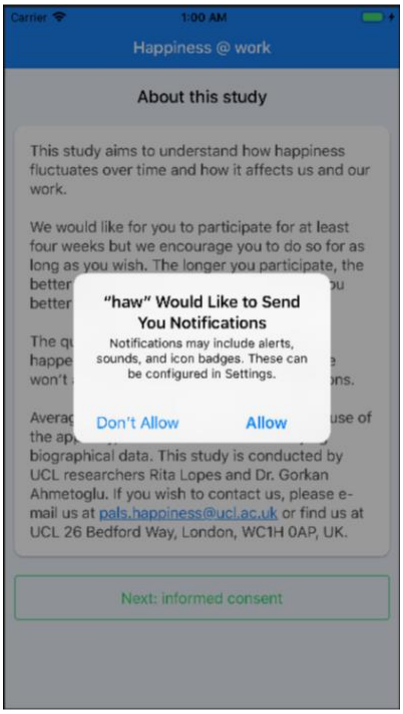
## Appendices

### *Appendix A – Welcome and information screen*

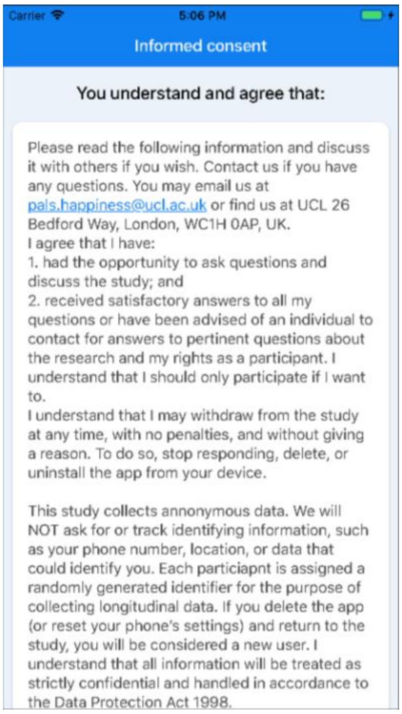
Screenshots of the “Happiness at work” Experience Sampling mobile app.

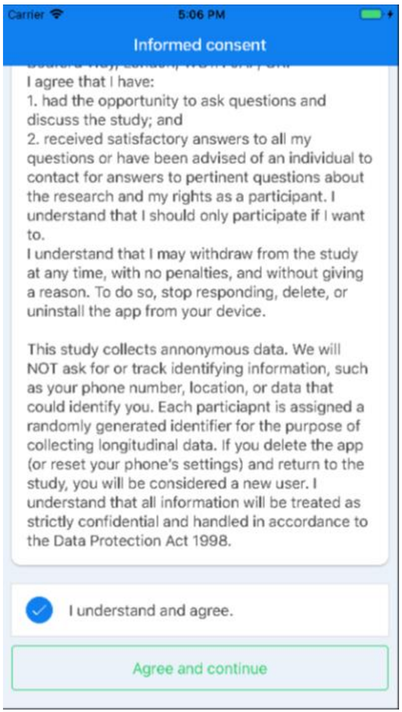
These are not exhaustive; they are intended as a general representation of the functioning of the app. They may not reflect the latest updates released to the users. This app was available on the app store (for iPhone users) and on the playstore (for Android users).

Screens 1 & 2: Loading & Permission request to send notification to the user

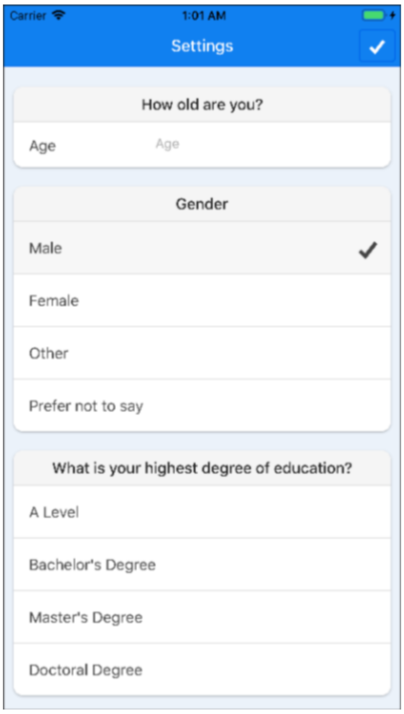



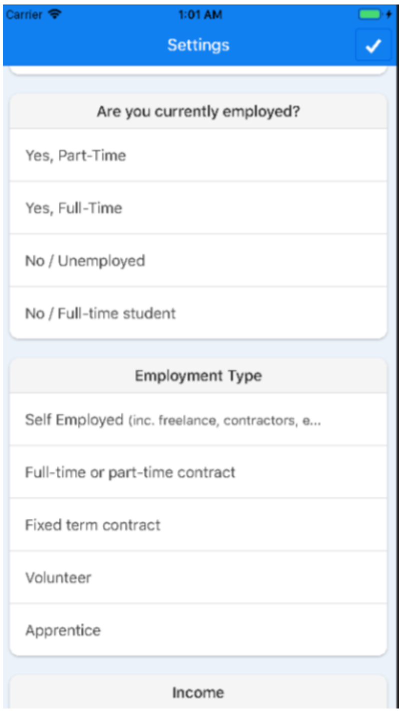
## *Appendix B – Informed consent*

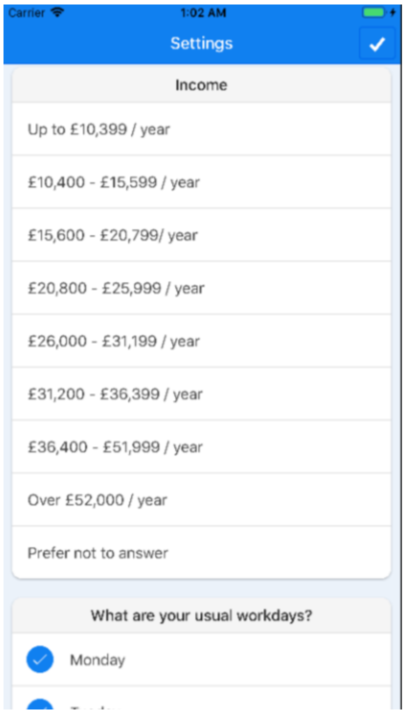


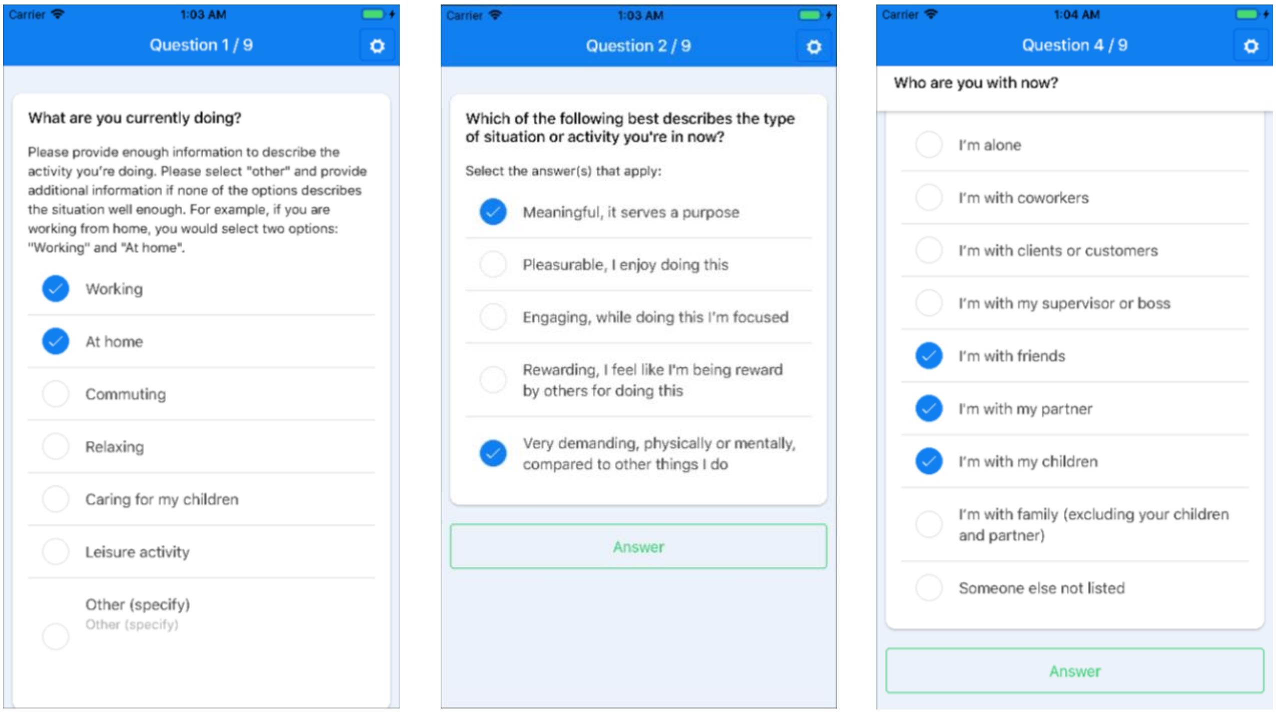
## *Appendix C – Demographic information*



## *Appendix D – Example questions – multiple choice answers*



## *Appendix E – Example questions – likert scales*