Emotions and Recidivism:

Exploring the Relationships between Dynamic Positive and Negative Affect,

Age, Gender

and Risk Categories with Recidivism Outcomes for Adults on Probation

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Abstract

Positive and negative emotions are known to be important motivators of human behaviour. However, there is a paucity of both theoretical consideration and empirical research related to whether individuals' dynamic experiences of positive and negative emotions could be statistically significant factors for predicting recidivism outcomes. To assist with addressing this research gap, the current study examined whether there is a significant relationship between adults' self-reported experiences of positive and negative affect over time on probation, as well as their age, gender and recidivism risk category, in relation to predicting their recidivism outcomes. This study was conducted as part of a larger multi-wave study of adults on probation from the United States (N = 352, N assessments = 650).

Three main objectives defined this project. Firstly, to examine which types of emotional experiences (e.g. according to their valence and behavioural activation dimensions) might demonstrate change during probation or predict recidivism outcomes. Secondly, to explore whether known static recidivism risk factors, such as participants' age, gender or risk category, may be associated with different degrees of positive and negative affect change over time. Thirdly, to explore whether a ratio of positive and negative affect, also known as the positivity ratio, would be a significant predictor of recidivism outcomes for the current study cohort of adults on probation.

The current study results have demonstrated that: (i) overall negative affect demonstrated significant change over 12-18 months for adults on probation, and had a significant predictive ability towards recidivism; however, this predictive ability was also adequately accounted for by the individual's recidivism risk category; (ii) overall positive affect demonstrated stability over 12-18 months for adults on probation, as well as significant predictive ability that was unaccounted for by the participants' recidivism risk category; (iii)

high behavioural activation negative affect (i.e., feeling uptight, angry, ashamed, stressed, nervous, guilty, and irritable) and the low behavioural activation positive affect (e.g. feeling calm, content, relaxed) emerged as particularly strong significant predictors of recidivism over and above the participants' recidivism risk category; (iv) participants within the high recidivism risk cohort displayed significantly higher increases in overall positive affect and near significantly faster decreases in overall negative affect over the 12-18 months on probation as compared to low-to-moderate recidivism risk group, indicating that high risk adults could represent a theoretically different group from the average population in terms of distinct patterns of positive and negative affect change over time; (v) PANAS positivity ratio did not emerge as a significant predictor of recidivism, when considered over and above its individual components, suggesting that a model focused on positive and negative affect separately may be a more useful way of exploring predictions of recidivism outcomes for adults on probation.

Despite the influence of emotions remaining mostly unaccounted for by current recidivism risk theoretic frameworks, the current study results suggest that adults' dynamic affective experiences (their overall positive and their highly activating negative affect in particular) predict adult recidivism outcomes, above and beyond of what is currently considered within standard risk frameworks. However, further research across both similar and diverse correctional samples is required, to both validate and explore generalisability of the current findings, before firmer conclusions on the nature of the links between adults' dynamic affective experiences and their recidivism risk can be drawn.

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impending birth in April 2021 had spurred on a flurry of writing activity which culminated with not one, but three finished chapters - including the dreaded Results - just in time for her arrival. This person pretty much deserves this PhD as much as I do, because she has lived through the ups and downs of it as viscerally as I did - so much so that she was basically born as Dr Ott.

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Marisa - this one is for you.

With love,

Your Mum.

22/07/2022

Neira Ott

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Chapter One: Introduction and Overview of this Thesis

Introduction

The Risk-Need-Responsivity (RNR) model is the cornerstone model for the assessment and treatment of youths and adults who offend offenders. The RNR model posits that criminogenic risk can be accurately assessed, and that rehabilitation is based on the proper recognition, categorisation and intervention approach of the risk and needs of youths and adults who offend (Blanchette & Brown, 2006; Ward, Mesler, & Yates, 2007). The *Risk* principle refers to matching the level of service to the offender's risk for recidivism, while the *Need* principle refers to assessing criminogenic needs and targeting them in treatment. Finally, the *Responsivity* principle refers to maximising the offender's ability to respond to a rehabilitative intervention by tailoring the intervention to the learning style, motivation, abilities and strengths of the youths and adults who offend (Bonta & Andrews, 2017).

While the *Risk* and *Needs* principles have been the focus of extensive research since the 1990s, a relative paucity of research remains in the *Responsivity* area of the model. Yet the understanding of factors driving offenders' responsivity to rehabilitative intervention is arguably important to them establishing ongoing desistance from crime, or "making good" (Maruna, 2001)

In the book based on his seminal research, Maruna (2001) defined crime desistance as the process of ongoing maintenance of crime-free behaviour in the face of life's frustrations. Studying desistance therefore means studying the factors supporting the continuity of non-deviant behaviour (i.e. *how* desistance is maintained over time), which could be very different from the factors that have initially influenced offenders' decision to change (i.e. *why* desistance was chosen) (Maruna, 2001). Thus, motivations for maintaining change (or responsivity toward engaging in change when facing challenges) are an under-studied component of a change process that the RNR model has attributed more simply to reductions in criminogenic needs.

Continuity research focuses on the personality variables, interactions and environmental consistencies that allow for long-term persistence in behaviour (Maruna, 2001). For example, research on alcoholism suggests that negative or ‘avoid’ motives, such as loss of a job or a relationship, might be the most common incentives for initiating change to abstinence from alcohol. However, it is the more positive or ‘approach’ motives, such as a sense of purpose or commitment to occupational success, that are more influential in successfully maintaining sobriety in the long-term and against powerful temptations (Earls, Cairns, & Mercy, 1993). In other words, positive ‘carrots’ are more motivating than negative ‘sticks’ when it comes to maintenance of desired behaviour through adverse times (Huta & Hawley, 2010).

Background and Research Rationale

Broadly, positive and negative emotions are known to be important motivators of human behaviour. However, there is a paucity of research exploring whether adult offenders’ experiences of positive and negative emotions could be significant factors related to their ability to remain abstinent from crime, or to predict their recidivism risk.

Positive emotions in particular have more recently become the subject of considerable attention within psychology. Positive psychology research focuses on the positive aspects of psychological functioning in the effort to better understand the promotive factors of individual well-being (Harris, Brazeau, Rawana, & Klein, 2017; Seligman & Csikszentmihalyi, 2014). This involves the study of positive emotions, character strengths, hope, gratitude, creativity, future mindedness, courage, spirituality, responsibility, etc. (Seligman & Csikszentmihalyi, 2014). A pioneer advocate for the utility of positive emotions, Fredrickson (1998) argued that positive emotions have a functional value beyond merely feeling pleasant by facilitating and building social connections and relationships. As part of Fredrickson's broaden-and-build theory, negative emotions are thought to narrow an individual's range of thoughts and actions, focusing their resources on survival, 'fight' and 'flight' behaviours (Fredrickson & Levenson, 1998). In contrast, experiences of positive emotions were postulated to momentarily broaden an individual's mindset, including available problem-solving thoughts and actions ("play" and "explore" behaviours), and by doing so to facilitate behavioural flexibility (Fredrickson, 2001, 2003). Moreover, Fredrickson argued that this can generate further upward spirals of positive emotions, cognitions and actions, allowing for ongoing personal development and transformation.

Thus far, empirical research has supported Fredrickson's broaden-and-build theory by demonstrating that induced positive affect has a wide variety of benefits including widening levels of attention (Fredrickson & Branigan, 2005; Rowe, Hirsh, & Anderson, 2007) broadening behavioural repertoires (Fredrickson & Branigan, 2005), increasing intuition (Bolte, Goschke, & Kuhl, 2003) and creativity (Isen, Daubman, & Nowicki, 1987). One of the most psychometrically sound and frequently used research measure of emotional appraisal is the revised Positive Affect Negative Affect Schedule (PANAS) (Watson, Clark, & Tellegen, 1988). Understanding of whether offenders' dynamic positive and negative affect might be related to their recidivism outcomes could be important and yet untapped factor for assessing and influencing individuals' risk of reoffending, or conversely, chances of desisting.

Additionally, the age-crime curve (ACC) postulates that individuals' age at offending is one of the most important factors related to likelihood of re-offending behaviour, with research consistently showing that desistance from crime becomes the norm as offenders age beyond their teens and early 20s (Hirschi & Gottfredson, 1983). In the present research, individuals' ages, as well as their gender and recidivism risk category, were also considered relevant when exploring links between positive and negative emotions and re-offending behaviour. As such, they were also included as moderating and prediction variables of interest in this study.

Research Aims and Methodology

The first aim of this study was to examine whether there is a significant relationship between adults' experiences of emotion over time on probation and their recidivism outcomes. If so, we explored which types of emotional experiences (e.g., their valence, activation level, or positivity ratio) might account for most of the predictive ability towards recidivism outcomes.

The second aim of this study was to explore whether participants' self-reported positive and negative emotional experiences during probation show any patterns of significant change over time, and if so, to describe them. As part of this aim, we also explored whether participants' age, gender or recidivism risk category may be relevant static factors that were associated with different degrees of participants' positive and negative affect change over time.

The third aim of this project was to explore whether a ratio of positive and negative affect, also known as the positivity ratio, would act as a significant predictor of recidivism outcomes for this study cohort of adults on probation.

Thesis Structure

The focus of this thesis is conducting exploratory analyses of self-reported dynamic positive and negative affect among adults on probation. A chapter-by-chapter summary is provided below.

Chapter 2 commences with an overview of the Risk-Needs-Responsivity (RNR) model, a cornerstone model for the assessment and treatment of offender populations. Notably, while RNR model has many strengths and evidence-based backing, one of its major criticisms is in being overly risk-management focused, whilst failing to account for individuals' strengths. The Good Lives Model (GLM) is discussed as an alternative to the RNR model which promotes focusing on positive 'approach' goals to motivate individuals' desistance, as opposed to RNR model's focus on the 'avoidance goals' of avoiding criminogenic risk factors. Chapter 2 next discusses theories of how desistance is achieved, and studies showing how the desistance process appears to be more motivated by positive 'approach' goals rather than avoidance goals. Furthermore, research on the main drivers for human behavior– cognitions and emotions - is briefly outlined, inclusive of the 'primacy debate' (which comes first, cognition or emotion?), as well 'the integration view' (both emotion and cognition are relevant across different levels of information processing). Further, research related to the specific influence of emotions on general behavior is also discussed, as well as the more limited body of knowledge regarding the influence of emotion on offending behavior in particular. While negative emotions are more commonly discussed in relation to motivating offending behavior, research related to the influence of positive emotions is notably scarcer, if not non-existent, within the criminology field. Yet the utility of positive emotions is recently emerging as more and more evident within the developing field of positive psychology, following on from the influential Frederickson's (1998) broaden-and-build theory of positive emotion.

Finally, a closely relevant previous research study by Brown, St Amand, and Zamble (2009) is specifically discussed in Chapter 2 with focus on their study results related to emotions and reoffending outcomes in adults on probation (Brown, St Amand, & Zamble, 2009). The current study is then introduced as partially an attempt to replicate Brown et al.'s (2009) results related to dynamic affective experiences for adults on probation. In addition to replication, the current study has also deepened the exploratory scope by examining two separate affective dimensions (valence and behavioral activation), and examining the potential moderating relationships of static recidivism risk factors, specifically participant's age, gender and recidivism risk category.

Chapter 3 presents the methodology used in this quantitative study. Data collection method - including participant selection criteria, recruitment procedures, measures used, and the study procedure - are discussed in sufficient detail so that the study could be replicated by others in the future. This chapter also discusses practical steps taken to minimize attrition. A section on data analysis is included to describe analytical approaches applied in this study and the rationale behind the statistical analyses chosen, given the sample specificity (adults on community probation) and the data structure (multi-wave study).

Chapter 4 presents the results section, which is organized so that results of the six affect domains were presented in order, from Negative Affect (Total, High Activation, and Low Activation); to Positive Affect (Total, High Activation, and Low Activation). Within each of these six affect domains, Chapter 4 first presents multilevel modelling results examining longitudinal change across time and interaction between time and age / gender / recidivism risk category, followed by the Cox regression analyses related to prediction of recidivism using each affect domain. Finally, Chapter 4 presents the positivity ratio results drawn from the Cox regression survival analyses, exploring whether the positivity ratio predicted recidivism.

Chapter 5 is the discussion chapter. This chapter brings together the study findings and explores these in relation to theory and previous research results. Tentative explanations are offered for the more surprising study findings, with a call for further research of self-reported affect within offender populations. Finally, there is a discussion on the strengths and limitations of the study, as well as a section on potential future research directions.

Chapter Two: Literature Review

The Risk-Needs-Responsivity (RNR) Model

The Risk-Need-Responsivity (RNR) model is the cornerstone model for the effective assessment and treatment of youth and adult offenders. The RNR model posits that criminogenic risk can be accurately assessed, and that effective rehabilitation is based on the appropriate consideration, categorisation and treatment of the individual's risk and needs (Andrews & Bonta, 1998; Blanchette & Brown, 2006; Ward, Mesler, et al., 2007). The RNR model is not a theory of intervention, but a theoretical viewpoint which outlines principles of effective offending intervention (Andrews & Bonta, 2003), within which a wide variety of therapeutic interventions can be used. Andrews and Bonta posit that offending behaviour and its drivers are multifactorial, and that a number of factors need to be considered in any comprehensive theory of criminal behaviour (e.g., temperament, biological, genetic, and social and cultural factors). This general outline of offending behaviour is referred to as Psychology of Criminal Conduct (PCC). Andrews and Bonta have further defined the three guiding principles of Risk, Need and Responsivity as guides for effective rehabilitation. These three principles, and the Risk and Needs principles in particular, have spurred decades of empirical research that has revolutionized the practice of assessment and treatment of offending populations (Looman & Abracen, 2013).

The Risk Principle

The risk principle relies on the accurate estimation of risk of future recidivism, followed by the appropriate matching of the intervention level and intensity to the predicted risk levels for each individual (Bonta & Andrews, 2017; Ogloff & Davis, 2004). The prediction of recidivism relies on the accurate identification and assessment of risk factors which have been empirically identified as related to risk of offending. The subsequent level of risk to level of intervention matching requires that the provision of treatment services remains proportionate with individual's recidivism risk levels (Simourd & Hoge, 2000). In practice, this means that individuals who are assessed to be at a higher risk of recidivism are provided higher level of services, while individuals with lower risk of recidivism should be given lower level of services aligned with their lower risk. Moreover, research has shown that lower recidivism risk individuals derive better results from less intensive levels of service and intervention (Bonta & Andrews, 2003). However, while the principle of risk-to-intervention matching is considered critical to the RNR model, in daily practice it can feel counterintuitive to the front-line clinicians, who might be more likely to pour their resources into the more motivated clients from the lower-risk categories (Ogloff & Davis, 2004).

Within the risk principle, individuals' risk of future recidivism is often routinely assessed via the application of structured, standardised recidivism risk assessment tools that are commonly used by the correctional staff across the Western world, especially in English-speaking countries. The application of a standardised risk assessment tool generally involves objective ratings about the individual with offending history using a variety of common and well-established recidivism risk factors. The recidivism risk factors are commonly divided into static and dynamic categories. Static risk factors are the biological or historical markers which are a part of an individual's life which cannot be changed, such as individual's gender, criminal history, early childhood exposure to violence, age at first offence, etc. In contrast, dynamic risk factors are aspects of an individual or their environment that still hold the potential to be changed, or that may remain stable over time despite holding potential for change (e.g., a person's association with anti-social peers, substance use, employment, education, and antisocial attitudes) (Andrews, Bonta, & Hoge, 1990). Predictive validity is similar for both static and dynamic risk factors when predicting future offending (Gendreau, Little, & Goggin, 1996). However, as static factors remain firmly unchangeable, the research and the offending rehabilitation focus has been aimed at both detecting and decreasing the presence of the dynamic risk factors in offenders' lives, ideally leading to a lowered risk of recidivism (or conversely, a longer period of desistance from crime). Although empirically relevant to efforts in reducing recidivism, the definition, theory and research about dynamic risk factors has not been without controversy (Polaschek, 2015). For example, as dynamic factors are by their definition changeable, Serin et al. (2015) argued that at least two (and ideally three) repeated measurements of a dynamic item are required over time to detect the process of change that would be relevant to changes in recidivism risk. In her recent review of the definition and concept of dynamic risk factors, Polaschek (2015) concluded that dynamic risk factors have to become better defined so that they can, for example, be distinguished by their location in the environment or person, be categorised as either aetiological to offending or have arisen secondary to other aetiological processes, and whether they are found as equally relevant at different stages of desistance from crime.

The Needs Principle

Humans have a range of needs that we are motivated to meet through action. Following on from Bandura's social learning theory (Bandura, Ross, & Ross, 1961), which emphasises the importance of learning through observation, modelling and reinforcement from others, Andrews and Bonta (2003) hypothesised that when human needs are being successfully met via anti-social behaviour, individual's criminal behaviour becomes positively reinforced as a useful way to meet their needs. For example, if a person struggles to develop friendships, and their need for belonging and acceptance is met by associating with antisocial peers, the person is more likely to also become antisocial in order to meet their need of remain accepted by the group (Andrews & Bonta, 2003). Offending behaviour can therefore be used as a direct or indirect means for meeting individual needs, such that the personal and interpersonal factors that reinforce offending as a behavioural option became known as "criminogenic needs".

Criminogenic needs are best distinguished from non-criminogenic needs when they are defined as those dynamic (changeable) risk factors that have been empirically found to relate to ongoing offending (Ogloff & Davis, 2004). The empirical relationship with offending is crucial, as individuals may have many needs deserving of treatment, but not all of these needs are associated with their criminal behaviour. Examples of needs which are not functionally related to offending behaviour, and are considered non-criminogenic, include self-esteem, anxiety, isolation, psychological discomfort, group cohesion, neighbourhood improvement, physical health (Bonta & Andrews, 2007; Ogloff & Davis, 2004). Conversely, the following eight risk/need factors (the "Big Eight") have been identified as central to the development and maintenance of offending behaviour: history of antisocial behaviour, antisocial personality patterns, antisocial attitudes, antisocial peers, substance abuse, poor marital / family relationships, poor work / school performance, and lack of prosocial activities. With the exception of history of antisocial behaviour, which is a static risk factor that cannot be changed, the other seven risk/need factors are considered to be criminogenic needs directly relevant to risk of offending, which should be targeted in recidivism treatments to reduce the risk of recidivism (Andrews & Bonta, 2003).

To further clarify the distinction between the criminogenic and non-criminogenic needs, consider the criminogenic need of antisocial attitudes and the non-criminogenic need of self-esteem. Reducing individual's antisocial attitudes (and improving their prosocial attitudes) through treatment would also reduce their likelihood of re-offending. However, increasing individuals' self-esteem in treatment, without supporting any changes in their antisocial attitudes, could help to create a more self-confident offender. Self-esteem is therefore considered a non-criminogenic need because changes in self-esteem will not reduce the likelihood of future criminal behaviour (Bonta & Andrews, 2007). The needs principle explicitly calls for re-offending treatment to be focused on accurately identifying and targeting empirically-supported criminogenic needs in treatment, in order to effectively reduce each individual's risk of recidivism.

The Responsivity Principle

The responsivity principle refers to maximising each individual's ability to respond to a rehabilitative intervention by tailoring the intervention to each individual's learning style, motivation, abilities and strengths (Bonta & Andrews, 2017). The responsivity principle is divided into two components: general responsivity and specific responsivity.

The general responsivity principle states that effective offending treatment interventions are most commonly based on cognitive, behavioral, and social learning theories (Smith, Gendreau, & Swartz, 2009). In particular, effective cognitive social learning strategies operate according to the following two principles: i) the relationship principle of establishing a warm, collaborative and respectful working alliance; and ii) the structuring principle of influencing the course of change through appropriate pro-social modelling, problem-solving, and positive reinforcement (Bonta & Andrews, 2007).

The specific responsivity principle focuses more on a person-specific consideration of each individual's strengths and personality when planning and implementing treatment interventions. The underlying idea behind specific responsivity is that treatment can be enhanced if the interventions are tailored to match the individual's personal factors which can facilitate learning. This requires consideration of a wide range of personal-cognitive-social factors in offending treatment (Bonta & Andrews, 2007). For example, treatment providers may first need to take into account and address an individual's mental health, to reduce their anxiety and enable the individual to attend and participate fully in a program targeting their criminogenic needs. Cognitive factors, such as limited verbal skills and a concrete thinking style, should also be taken into account. Treatment programs should also be adapted to minimize the presence of overly-abstract concepts which individuals with a more concrete cognitive profile will struggle to learn from, instead placing higher emphasis on behavioural practice (Bonta & Andrews, 2007). Identifying and reducing any personal, social, or cultural barriers to attending treatment could also improve offending rehabilitation outcomes. This may be vital for engagement and motivation of women with a history of offending (e.g., through providing child care so the mother can attend treatment) and for Aboriginal individuals with offending histories (e.g. through including Elders and spiritual ceremonies along with structured cognitive behavioural treatment) (Bonta & Andrews, 2007).

Critiques of the RNR Model.

Despite its undisputed popularity and empirical support (Dowden & Andrews, 1999; Hanson, Bourgon, Helmus, & Hodgson, 2009), the Risk-Needs-Responsivity model has also been subjected to criticism over the last two decades, particularly by Ward and colleagues (Ward & Laws, 2010; Ward, Mann, & Gannon, 2007; Ward & Stewart, 2003a, 2003b), who argued that the RNR model, despite its empirically proven strengths, has areas of weaknesses. In particular, Ward, Mann and Gannon (2007) criticized RNR model as being overly risk management-focused, and conceptualising the individuals as “disembodied bearers of risk”, with their treatment focused on removing the risk factors and failing to take a more integrated, holistic approach to the individual that would also include their strengths (Ward, Mann, et al., 2007). They further suggested that RNR model takes a reductionist approach which addresses only the criminogenic needs, and in doing so fails to address the important wider factors of human agency, goals and personal identity. Additionally, Ward and colleagues argued that the RNR model disregards wider human needs and their influence on the offending behaviour, alongside the influence of the therapeutic relationship between offending individuals and clinicians, or the therapist-specific factors such as their attitudes towards offending behaviours. The RNR model’s apparent emphasis on risk management was also thought to assist with the formulation of negative, avoidance-based goals which are viewed as not motivating enough for individuals to maintain abstinence from offending in the long-term (Ward, Mann, et al., 2007). Lastly, it could be argued that there is a distinct lack of attention paid to individual's affect and emotions within the RNR model, whereby emotions have been largely unaccounted for in the RNR model due to focus on the cognitive and behavioural risk/need factors that have been identified as central to the development and maintenance of offending behaviour (e.g., the history of antisocial behaviour, antisocial personality patterns, antisocial attitudes, antisocial peers, substance abuse, poor marital / family relationships, poor work / school performance, and lack of prosocial activities).

As an alternative view that could augment the RNR model, Ward and Stewart have proposed The Good Lives Model (GLM), a strengths-based offending rehabilitation framework that aims to provide individuals with external and internal resources to build new identities, based on positive goals that are inconsistent with future offending (Ward & Stewart, 2003a, 2003b, 2003c).

The Good Lives Model (GLM)

In the Good Lives Model, an individual is hypothesised to start offending because they lack skills to achieve one or more of the Primary Human Goods in a socially acceptable ways (Ward, Mann, et al., 2007). The model assumes that all individuals have similar aspirations in life, which are often summarized as the eleven Primary Human Goods: life (including healthy lifestyle and functioning), knowledge, excellence in work and play (including mastery experiences), excellence in agency (autonomy and self-directedness), inner peace (freedom from emotional turmoil and stress), relatedness (including intimate, romantic and family relationships), community, spirituality (broader sense of finding a purpose in life), pleasure (happiness in the here and now), and finally, creativity (Looman & Abracen, 2013; Ward, Mann, et al., 2007). The main focus of the GLM model is on individual's strengths-based rehabilitation based on each individual's specific interests, aspirations and abilities. The model directs practitioners to construct treatment intervention plans that focuses on using individual strengths to achieve goals that are personally meaningful to them (Ward & Laws, 2010). In this way, the GLM promotes an increased focus on the ‘approach goals’ to motivate individuals’ desistance, as opposed to focusing on the ‘avoidance goals’ of avoiding criminogenic risk factors, which was identified as a relative weakness of the RNR-model. In addition to being strengths-focused, the GLM is also personal agency-centred because it works on recognising and enhancing individual’s ability to select personally-valued goals, formulate appropriate plans and act freely in the implementation of these plans. The combined personal strengths and agency-centred approach is aimed to assist individuals in reaching desistance through building an alternative, pro-social identity, inconsistent with continued offending. In support of this idea, empirical research has shown that a crucial factor for long-term motivation and maintenance of desistance from offending is establishment of an internal shift in how individual views themselves (Maruna, 2001). Maruna and Roy (2007) further noted that “knifing off the past”, i.e., rejection of offending behaviour, which is considered a desistance-influencing factor, is rarely mentioned without also including mention of “providing scripts for the future”. This, thus, points to the significance of change in life scripts for constructing a non-criminal future. They argue that without a creation of a new, pro-social self-narrative to replace the offending self-narrative, individuals’ efforts towards “knifing off the past” would not necessarily produce a lasting behavioural or personality change (Maruna & Roy, 2007).

One advantage of the GLM is that it adopts a more holistic approach than the RNR model. Firstly, it is focused on assessing personal individual strengths and values as a way of helping people achieve desired goals, as well as increasing their happiness levels, through engagement in alternative, pro-social behaviours. Secondly, one of the general ideas of GLM is to assist individuals to achieve pleasure, i.e. to feel good in the here and now, as part of the

Eleven Primary Human Goods. The GLM model therefore explicitly outlines the potential importance of both accounting for and harnessing individuals' positive affect during the rehabilitation process, as a way of increasing their engagement in both the rehabilitation program, and in the new forms of pro-social behaviour. This is a relatively novel contribution to the field of rehabilitation from offending, mainly because it explicitly refers to the utility and relevance of paying closer attention to emotions as a way of reducing individuals' recidivism risk, with affective focus remaining a potentially missing link in the well-established RNR model. Notably, the GLM focuses only on the potential importance of positive affect in relation to offender rehabilitation, thus failing to account for negative affect and how it might also be relevant to recidivism risk.

The RNR vs GLM Approaches

In their comprehensive review of the RNR and GLM approaches in correctional treatment, Looman and Abracen (2013) analysed whether there is a need for a new model of offending rehabilitation. Their broad review suggested that, while there was a wealth of research in support of the RNR approaches with female, violent and sex offenders, a relative paucity existed of the available research demonstrating the efficacy of the GLM approach in the same populations. They further suggested that the main assertions of the RNR and GLM models are in fact similar, but are presented through two different lenses – while the RNR model proposes that offending occurs when the personal, interpersonal and community supports for behaviour are favourable to crime, the GLM proposes that offending arises from person's attempt to relieve a sense of incompetence and dissatisfaction from not acquiring the basic human goods. Other similarities between the RNR and GLM have also been noted in the recent excellent review by Wormith and Truswell (Wormith & Truswell, 2022). However, the perspective difference is that RNR model employs a cognitive-behavioural approach, while the GLM advocates for a more humanistic orientation to offending behaviour. It was further noted that the RNR model uses predominantly deficit-focused language, as opposed to the more strengths-based language of positive psychology employed by the GLM when working with individuals who engage in offending, which was seen as potential area of improvement for the RNR model. Despite concluding that at the time there was not enough research evidence that the GLM approach is effective, or that it should replace the RNR approach, the authors' view was that the RNR model would also benefit from a revision which takes into account the newer empirical findings related to factors which were also found to be associated with recidivism (e.g., therapeutic alliance, past trauma, adverse developmental experiences and mental illnesses), which although relevant, are not included in the RNR model. Interestingly, most of these newly identified but relevant recidivism risk factors, which are yet unaccounted for in the RNR model, also revolve around individual's experience of, and ability to manage their negative emotions, again pointing towards a gap in the RNR model in relation to accounting for the emotional experiences of offending individuals. Following on from this, the same additional factors were recommended as areas to be addressed in treatment by the clinicians working in the field (Looman & Abracen, 2013), as addressing these additional factors would likely assist in further reducing the risk of recidivism, or conversely, increasing individual's chances of establishing their ongoing desistance from crime. In both RNR and GLM approaches, however, it would appear that substantial gaps remain in adequately accounting for the potential role of offenders' emotions, both positive and negative, in predicting and managing their recidivism risk.

Desistance from Crime or "Making Good"

How do we define desistance from crime? In the criminological literature, desistance from offending behaviour has been a complex construct to define. It has been conceptualised as the psychological process associated with staying crime-free, or an outcome related to the appearance of a arbitrarily defined period of offending-free activity, or a combination of both (Polaschek, 2015). Two types of desistance were identified: primary desistance - or any cessation of offending behaviour that occurs without individual's self-awareness or active input being required, usually over shorter periods of time; and secondary desistance - a longer period of non-offending that is accompanied with individuals' active desistance awareness and /or an identity change within the individual (Maruna, 2004). Serin and Lloyd (2009) have further conceptualised desistance as an outcome which follows an achievement of a certain level of psychological change, such as establishment of new pro-social habits, legitimate employment and improved self-regulation skills (Serin & Lloyd, 2009). It was further suggested that desistance definitions should also consider the complex interplay of individual's offending career lengths and the type of offending they engaged in. For example, among individuals who engaged in infrequent offending, longer desistance periods may be required to define achievement of later stages of desisting. Also, depending on their offending history, some individuals may define desistance as giving up all but most trivial forms of crime, as opposed to there being a complete absence of offending (Polaschek, 2015). Therefore, desistance could also be conceptualised as a dynamic time-based process of movement from higher level of offending to a 'not significantly different from zero' levels of offending (Paternoster & Bushway, 2009). However, stopping and restarting of offending is common, but due to limited research on recidivism patterns over lifetime (especially in the later stages), it is difficult to determine what phase of desistance each individual is presenting in when they are crime-free (Piquero, 2004).

Regardless of how desistance is defined, it is well known in the criminology literature that the eventual desistance from crime is the norm, as sooner or later almost everyone participating in serious offending gives it up and desists. This finding has been well-documented by the decline element of the age-crime curve, which has been carefully examined in the past 80 years and found to apply to individuals of all types (Glueck & Glueck, 1950, 1968; Laub & Sampson, 2003; Polaschek, 2015; Sampson & Laub, 1993). This is also consistent with Moffitt's (1993) observation related to youth delinquency, where she noted that the majority of youth with a history of offending will quit crime in their early 20s (Moffitt, 1993).

Desistance Factors

If desistance from crime becomes the norm as individuals with offending histories age, how is it achieved and maintained? Desistance studies have demonstrated that ceasing crime requires a behavioural change which is often facilitated by both internal and external events in individual's life. These events have been separately referred to as "turning points" (Laub & Sampson, 2003; Sampson & Laub, 1993), "hooks for change" (Giordano, Schroeder, & Cernkovich, 2007), or "making good" (Maruna, 2001). Research literature on desistance from crime has defined 12 possible factors that appear to have an important influence on individuals' ability to desist: aging (most powerful influence affecting behavioural capacity in general), marriage (social event creating new responsibilities towards a family), employment stability (increasing social contact with conventional others), military service (development of discipline, tolerance and personal responsibility), juvenile detention (teaching importance of adhering to rules), prison, education (leading to stable employment and family formation), cognitive transformation (creation of a coherent new pro-social identity), the 'Pygmalion Effect' (being subject of high expectations of others leading to higher self-belief that helps to evoke change), 'knifing off' (cutting bonds with criminal past), spirituality, fear of serious assault or death, and serious incapacitation (Ward & Laws, 2010).

Theories of Desistance

Two main desistance theories have emerged over time. The first has focused on the influence of environmental social control factors on individuals' behaviour (Sampson &

Laub, 1993), and the second has focused on the internal psychological processes related to human agency, and their influence of individuals' behaviour (Maruna, 2001). In the first theory of desistance, Sampson and Laub (1993) emphasised the importance of external 'turning points', or significant societal events such as achievement of a stable employment or marriage, which in turn interrupts future offending. They argued that behavioural change results from an individual's involvement in conventional societal roles (e.g., taking a role of a stable worker or a good husband), with desistance from crime often resulting from the role changes without the person actively planning for or participating in it. This is also known as 'desistance by default', or desistance that is not actively intended by the individual. The authors additionally acknowledged the important role of external societal factors, such as family, school and social environment especially in the early years, as offending was more likely to occur when these social bonds were interrupted or broken early (Sampson & Laub, 1993).

In contrast to Simpson and Laub, Maruna (2001) studied and compared the differences in the internal, psychological self-narratives of crime 'persisters' vs crime 'desisters'. He found that each group developed distinctive narrative scripts. The narrative of persisters was termed the 'Condemnation Script', in which crime persisters viewed themselves as helpless, dependent of external circumstances and as victims of society. Conversely, the narrative of crime desisters was termed the 'Redemption Script', where desisters viewed themselves more optimistically than persisters, e.g., as having the ability to control their own lives, to be productive and to give back to society. Ultimately, Maruna (2001) concluded that while external social factors (e.g., marriage, employment) have an important influence on promoting desistance from offending, the most important factor in achieving successful desistance was the human agency through a generation of a new, internal, pro-social identity self-narrative underpinning ongoing desistance. In particular, Maruna also concluded that individuals with offending histories who ‘make good’ do not go on to form a new, pro-social identity after completely renouncing their anti-social identity (known as ‘knifing off’). Instead, his research has demonstrated that individuals who hold current prosocial views of themselves came to that point by deliberately distorting their criminal pasts, to make their past offending actions explicable and consistent with their current positive view of who they ‘really are’ (Paternoster & Bushway, 2009). In other words, desisters tend to reconstruct their offending past in their minds via a novel narrative that explains how their past offending behaviour has led to them to re-discovering who they really are, i.e., rediscovering their pro-social selves (Maruna, 2001).

In a more recent conceptualisation of desistance from violent behaviour in adolescence, which incorporates elements from both two main theoretical desistance streams, it was proposed that desistance is a dynamic process that arises from two complementary developmental processes – first, the transition from external to internal self-controls, and the second, the development of behavioural and emotional controls (Loeber, Pardini, Stouthamer-Loeber, & Raine, 2007). The first process refers to the gradual transition from a childhood full of external controls (imposed by parents, teachers, peers) aimed at inhibiting aggressive impulses, to an adolescence with emergence of internal controls to inhibit aggression (Werner, 2005). It was argued that to complete successful socialisation, adolescents must learn to refrain from violence in the absence of the external influences, and develop reliance on the implementation of internal controls (Loeber et al., 2007).

The second growth area relates to the development of behavioural and emotional controls of aggressive behaviours. Behavioural controls refer to individuals finding alternative non-violent ways to resolve conflict (e.g. by negotiation, ignoring or delaying their response) rather than resorting to violence. Emotional control refers to adolescents developing self-control necessary to transform anger or irritation into more adaptive emotions

(Masten & Coatsworth, 1998). Both behavioural and emotional controls were postulated as being the key to a successful transition from reliance on external controls, to reliance on internal controls to inhibit violence (Loeber et al., 2007). The successful transition from external to internal controls of behaviour entails significant psychological growth in adolescents; requiring them to recognise their emotions as they arise, to moderate their cognitive responses so they lead away from anti-social themes, and ultimately, to learn new behaviour options and transform their behavioural responses. Generally speaking, successful emotion and cognition management therefore appears to be the key to subsequent behavioural changes, including for individuals who are moving from anti-social to pro-social behaviour. In the following section, we will examine what constitutes emotions and cognitions, and how they might influence behavioural outcomes.

Emotions and Cognitions

The cognitive revolution, or the focus on the cognitive information processing within the science of psychology, originated as an alternative to the dominance of behaviourism (the view of psychology as a science of observable behaviour), which had dominated psychology in the middle of 20th century (Miller, Flory, Lynam, & Leukefeld, 2003). The main goal of cognitive psychology was to map the ways in which humans collect, interpret, store, and modify information received from their environment, or of the pre-existing information which has been stored internally (Lachman, Lachman, & Butterfield, 1979). By definition, cognition refers to a group of processes such as attention, language, planning, memory, problem solving etc., many of which are considered to be distinctive to human beings (Pessoa, 2008). A common metaphor for the human mind, as inspired by the cognitive approach, has been the computer - mirroring the scientific focus on mind's analysing capabilities, with the influence of emotions on both cognitive processing or behaviour remaining largely ignored, as they were seen as only a by-product of cognitive evaluations (Phelps, 2006).

Emotion vs. Cognition – The Primacy Debate

Following a period of cognitive psychology dominance and the focus of psychological research on cognitive capacities of the human mind, the potential importance of human emotion came back into the spotlight of the psychological scientific discourse through a famous debate which occurred in 1980-1982, known as the 'cognition-emotion primacy debate'. The question of which comes first in the brain's processing of events – emotion or cognition - was hotly debated during those times, and in the decades following (Bozinovski, 2018). The American psychologist Zajonc (1980) had interrupted the established scientific discourse by arguing for the primacy of emotions in the brain, asserting that emotions arise independently of cognition and are potentially carried by separate neural systems. At that time, his view was contrary to the popular cognitive psychology view in which emotional reactions were considered to be only a by-product of the cognitive evaluations processes. Zajonc argued against this, and summarised the essence of his emotion-primacy argument in the title of his article: "Preferences need no inferences" (Zajonc, 1980).

In a reply to Zajonc (1980), American psychologist Lazarus (1982) argued for cognitive primacy, claiming that brain's cognitive functions are primary, and in fact a necessary component of the subsequent affective response. He noted that the cognition-affect relationship is so strong that affect could not be considered independent (Lazarus, 1982). Their debate attracted a lot of scientific attention, and culminated in a simultaneous publications of both arguments side by side in American Psychologist (Lazarus, 1984; Zajonc, 1984), with both authors continuing to hold their respective grounds but ultimately calling for increased empirical enquiry into cognition and emotion, to better define and understand how they interact.

One specific reason for advocating for the distinction between emotional and cognitive processing has been related to the anatomy of the brain, as different anatomical brain structures have over time been discovered as relating to either emotional or cognitive information processing. The idea of brain being functionally localised has been noted since at least the 1800s, when French doctor Pierre Paul Broca (1824-1880) reported language processing impairments in two of his patients who suffered lesions to the posterior inferior frontal gyrus (also known as Broca’s area) in their dominant hemisphere, which led to them developing post-injury deficits in language production (also known as Broca’s aphasia). Subsequent studies have provided evidence of cognitive processing being localised mostly in the cortical regions, e.g., sustained firing of dorsolateral prefrontal cortex cells was discovered to be a neural correlate for monkeys who were maintaining information in their working memory (Fuster & Alexander, 1971), and functional MRI studies have linked a variety of cognitive processes to various cortical regions (Gilbert, Zamenopoulos, Alexiou, & Johnson, 2010; Levine & Craik, 2012; Nestor et al., 2013). In contrast, research has linked emotional processing with various sub-cortical regions, e.g. the amygdala (Hrybouski et al., 2016; Mason et al., 2015; McCrory et al., 2013), hypothalamus (Frol'kis, Artemenko, Gerasimov, Dubiley, & Rushkevich, 1995; Silva et al., 2016; Yang et al., 2017) and ventral striatum (Hwang et al., 2016; Jastreboff, Lacadie, Hong, & Sinha, 2009; Satterthwaite et al., 2011). The ‘emotional brain’ structures have been thought to operate in a fast, automatic fashion so that stimuli which may be important for individual’s survival (e.g. the white of eyes in a fearful expression of another) (Whalen et al., 2004) are processed quickly, without much filtering and often below the conscious awareness of the individual (Pessoa, 2008).

However, over time, the advances in cognitive neuroscience research techniques have brought an increased clarity to the relationship between emotion and cognitions in the human brain. The early neuroscience research efforts were inspired by studies conducted with non-human animals such as rats, and therefore focused on the primacy of emotion as opposed to any cognitive processes (Phelps, 2006). For example, in non-human animal studies, early detection of emotions was found to be supported by the specialised subcortical pathways, allowing amygdala to detect environmental threats even before the standard perception pathways have been completed (Romanski & Ledoux, 1992), adding support to the emotion primacy hypothesis. Subsequent research in humans, which was conducted using functional magnetic resonance imaging (MRI), has provided further support to the existence of an equivalent pathway in human brains (De Gelder, Vroomen, Pourtois, & Weiskrantz, 1999; Pessoa, McKenna, Gutierrez, & Ungerleider, 2002). Taken together, these studies have provided providing support to the Zajonc's assertion that emotion processing can occur prior to cognitive processing. Further, human neuroscience research had focused on the amygdala, which was as a centre of automatic processing of emotions in humans (particularly fear) without the influence of awareness (Morris, Öhman, & Dolan, 1998; Whalen, 1998) or attention (Anderson, Christoff, Panitz, De Rosa, & Gabrieli, 2003; Vuilleumier, Richardso, Armony, Driver, & Dolan, 2004). For example, Whalen et al. (2004) tested the hypothesis that the larger size of eye whites (sclera), indicating a wide-eyed fear response, would be sufficient to modulate the amygdala responsivity in a backward masking study (stimuli presented very briefly then 'masked' by longer presentation of another image that can be consciously processed by the participants). Whalen and colleagues (2004) presented a simple eyes-only image to 20 participants during fMRI imaging, half of whom viewed neutral face mask presentations which were preceded by millisecond presentations of fearful eyes with larger scleras, while the other half were primed with the happy eyes with smaller scleras. All participants reported being unaware of the presence of the target eye stimuli prior to seeing the mask stimuli. The study results showed that the ventral amygdala signals were significantly larger in response to fearful than to happy eye whites, indicating that as little information as just the size of eye sclera is sufficient to produce an amygdala response, prior to any other conscious processing (Whalen et al., 2004). In summary, empirical evidence has slowly amounted indicating that cognitive functions such as human perception, memory and attention, appear to be influenced by the amygdala's very early emotion processing (Phelps, 2006), in alignment with the emotion primacy theory (Zajonc, 1984).

However, another strand of research on the amygdala has revealed that cognitive processes can in fact modulate the amygdala activity, thus changing the subsequent emotional experiences of the individual (Phelps, 2006). For example, Ochsner et al (2002) conducted a study where participants were shown images of emotional reactions (e.g., a female crying outside of a church). They had two experimental conditions: 'attend trials', where participants were asked to allow themselves to emotionally respond to the presented image and be aware of the feelings without changing them; and secondly, 'reappraise trials', where participants were asked to reinterpret the context of the photos (e.g., a female crying outside of the church as crying from joy as her child just got married). Generally, deliberate cognitive reappraisal is defined as the 'cognitive transformation of emotional experience' by giving a new meaning to the situational context (Ochsner, Bunge, Gross, & Gabrieli, 2002). In this study, reappraisal was found to be successful for the most negative photos, such that the degree of negative affect was significantly lower on 'reappraise' trials than on 'appraise' trials. The brain areas which have been implicated in the reappraisal process through the fMRI imaging were the increased activity in the medial and lateral prefrontal regions, as well as the decreased activity of the amygdala and the medial orbitofrontal cortex. These results provided evidence indicating that the prefrontal cortex drives the cognitive reappraisal of situations, which in turn modulates the activity of several emotion-processing brain regions (Ochsner et al., 2002), providing evidence in support of the cognitive primacy view.

In another example of cognitive reappraisal, Wheeler and Fiske (2005) asked participants to view photos of Caucasian and African-American individuals, and complete three tasks. In the socially neutral visual task, participants were asked to determine whether a dot was present somewhere on each person's face; in the social categorization task, to guess whether a person is over 18 years of age; and in the social individuation task, to decide whether the person on the photo would like a particular vegetable indicated by a word presented before the photo. The last condition encouraged participants to consider each person on the photo as a unique individual with unique preferences, rather than just belonging to a social or biological category. Tasks were completed inside an fMRI scanner, allowing researchers to measure activation of different brain regions. Their results showed that the basic categorical processing of social targets created different responses to in-group and out-group members in the amygdala. However, changing the social-cognitive goals in a way that required participants to consciously individuate people on the photos by considering their personal preferences reduced the out-group perceptions. This lead to a conclusion that amygdala (fear) responses to racial out-groups were not set in stone, rather, they depended on the viewer's current social-cognitive goals (Wheeler & Fiske, 2005). This finding has also supported the cognitive primacy view.

The debate of primacy of emotions vs. cognition in the brain has been a product of the traditional view that emotion and cognition arise from distinct, separate and competing areas and processes in the brain. Contributing to this classical view were the early brain imaging studies showing that regional blood flow decreased in the amygdala, orbitofrontal cortex, and ventral-medial prefrontal cortex during cognitive tasks, whereas blood flow had increased in those areas during emotional tasks (Drevets & Raichle, 1998). A complimentary reciprocal pattern was discovered in a study by Mayberg et al (1999), where blood flow decreased in the amygdala, orbitofrontal cortex and ventral-medial prefrontal cortex, but increased in the dorso-medial and dorso-lateral prefrontal cortex during cognitive tasks. These results led to a conclusion that cognitive and emotional processes engage in antagonistic interactions (Drevets & Raichle, 1998).

Emotion and Cognition - The Integration View

Regardless of the debated issue of emotion vs. cognition primacy, the empirical evidence has also been mounting in the support of overall integration between emotion and cognition in the brain. Integration has been generally defined as a merger of specialised sub-functions into a more generalised single function (Pessoa, 2015). When related to emotion-cognition combination, integration has also been defined as evidence of a brain region having crossover interactions that include both cognitive and emotional factors, but without any main effects of either. Presence of such a specific pattern within a brain region would indicate that cognition and emotion could be mostly separable until a certain level of processing is reached where functional specialisation is lost, when the two become integrated and thus inseparable. From that point on, emotion and cognition could be seen as co-jointly contributing to the control of thought, affect and behaviour (Gray, Braver, & Raichle, 2002).

The emotion-cognition integration view has also arisen due to the growing evidence of structural and functional brain interconnectivity, which has opposed the original views of functional localisation in the brain. Based on the mounting evidence that cognition and emotions share brain systems, Pessoa (2013) argued that emotion and cognition interact in ways that guide more efficient behaviour, rather than compete and antagonise each other (Pessoa, 2013). Examples of the evidence for emotion-cognition interconnectivity includes study findings of hypothalamus (which has traditionally considered important for emotion processing) providing direct contribution to the entire frontal cortex (Risold, Thompson, &

Swanson, 1997), and amygdala (also considered primarily an emotion processing centre) being identified as one of the most highly connected regions of the brain, projecting information towards the majority of the cortical brain areas (Barbas, 1995; Swanson, 2003). The amygdala was also found to project extensively into the brainstem and the lower brain regions that mobilize the body for action. As such, the amygdala and its connections across the brain have been suggested as strategically positioned in order to "ignite" both body and the brain (Pessoa, 2015). Gray, Braver and Raichle (2002) have utilised fMRI to explore the joint effects of emotional state manipulation and a cognitive task on brain activity in the lateral prefrontal cortex (PFC), which they considered to be a potential integration site for cognition and emotion. Their results showed a crossover interaction with no main effects, leading to conclusion that participants' lateral PFC neural activity was dependent equally and co-jointly on the emotional and cognitive stimulus condition. This finding has supported the identification of lateral PFC as a brain region sensitive to integration of emotion and cognition, with such activity influencing behaviour (Gray et al., 2002).

Gray et al (2002) have also suggested that integration does not mean that emotion and cognition are intrinsically and absolutely interconnected, rather, they may be separate processes until they are integrated, also with multiple processing streams possibly being present for both emotion and cognition, not all of which are integrated. According to Gray et al.'s model of emotion-cognition interaction, emotions could be seen as transitionally improving or impairing certain functions (but not others), and doing so in a quick, dynamic and reversible way, with an aim of biasing cognition and behaviour to more effectively meet the current situational demands (Carver, Sutton, & Scheier, 2000; Gray, 1999, 2001). Following on from the research looking into ventral-emotion vs dorsal-cognition organisation in the human brain, a large meta-analysis of both human and animal literature on the role of the medial PFC in emotion concluded that both dorsal and ventral-medial PFC make prominent contributions to emotional processing (Etkin, Egner, & Kalisch, 2011), providing evidence for emotion-cognition integration processing. Also, in a comprehensive meta-analysis of human neuroimaging studies by Shackman and colleagues (2011), a significant overlap was found between areas of medial PFC which were active during both negative affect and cognitive control (Shackman et al., 2011). In summary, contemporary neuroimaging research has shown that significant portions of PFC, including medial and dorsal, have been found active during emotional processing, overall favouring the perspective that medial PFC is shared by both cognitive and emotional domains in a way that supports adaptive control of complex behaviour (Pessoa, 2015). This is relevant for our overall understating of how both emotions and cognitions carry contributions towards determining complex human behaviour, rather than cognitions only. The focus of the next section will be on reviewing research on the ways in which emotions exert influence on both cognitions and behaviour.

Influence of Emotion on Cognitions

How do emotions influence cognitions? An interesting line of research has emerged describing influence of both conscious and unconscious emotional states on high-level cognitive functions. Empirical evidence has shown that mood affects how people process information, demonstrating that information processing is more careful when the information is consistent with individual's mood, as opposed to when mood is incongruent with cognitive input. Current mood was also found to assist with the facilitation or retrieval of mood-congruent information from memory, as well as with the formation of new cognitive evaluations which are congruent with the current mood (Martin & Clore, 2001). In particular, the effects of mood on cognitive judgements were found to be dependent on the level of cognitive processing that was required. The more extensive cognitive processing was required to formulate an output, the higher was the likelihood that mood will influence the cognitive processing outputs (Bower & Forgas, 2000; Forgas, 1995). For example, a relatively simple implicit memory task, such as identifying a word presented for milliseconds on a screen before it was masked, was not affected by mood. However, when participants were tasked with forming word associations or finding words that fit a definition, both cognitively more elaborate tasks, their current mood significantly affected their cognitive task performance (Watkins, 2002; Watkins, Martin, & Stern, 2000).

Research on the influence of the experimentally-induced happy and sad moods on cognitive performance has also demonstrated that moods can influence cognition regardless of whether they were pre-existing and unrelated to the current cognitive task, or whether they were elicited by the experimental stimulus. Moreover, the influence of mood on cognition persisted even when participants were consciously unaware of the mood (Martin & Clore, 2001). For example, research on language comprehension – a cognitive process which has traditionally been viewed as minimally influenced by affect – has shown some surprising results. Readers who have been experimentally induced into a happy or sad mood have judged a mood-incongruent story ending as significantly more surprising than a mood-congruent ending, which was noted both in the deliberate post-reading reflections on the whole story (Egidi & Gerrig, 2009), as well as in participants' neural reactions during the moment-to-moment integration of the story ending (Egidi & Nusbaum, 2012).

The Evaluative Space Model (ESM) - Negativity Bias and Positivity Offset

Also important when considering emotions and cognition, humans have a heightened sensitivity towards negatively valanced information, with this sensitivity present at different levels of cognitive processing (Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001). In other words, human attention is more captivated by, for example, a single criticism as opposed to five positive evaluations received in a work performance review. This phenomena has been defined as the attentional 'negativity bias'. Research has repeatedly indicated that negative information is automatically more attended to and subsequently more used in thinking, learning and communicating than equivalent positive information (Baumeister et al., 2001; Bebbington, Macleod, Ellison, & Fay, 2017; Morewedge, 2009; Rozin & Royzman, 2001). In other words, negativity bias suggests that in the moment of the event, losing $20 (an aversive stimuli) will feel more extreme and command more attention than a comparably good outcome, such as gaining $20 (Baumeister et al., 2001; Rozin & Royzman, 2001). Furthermore, a meta-analytic review found that negative emotions elicited more consistent and stronger physiological responses than positive emotions in adults (Cacioppo, Berntson, Larsen, Poehlmann, & Ito, 2000), and a review of multiple developmental studies showed evidence of the attentional negativity bias being present from infancy (Vaish, Grossmann, & Woodward, 2008). Moreover, previous studies have found that negativity bias has a significant influence on psychological functioning over the lifetime, particularly related to depression and anxiety (Bar-Haim, Lamy, Pergamin, Bakermans-Kranenburg, & Van Ijzendoorn, 2007; Gollan et al., 2016; Koster, Fox, & MacLeod, 2009; Macleod, Mathews, & Tata, 1986), evaluative categorizations (Ito, Larsen, Smith, & Cacioppo, 1998), judgement and persuasion (Herr, Kardes, & Kim, 1991), interpersonal impression management (Peeters & Czapinski, 1990), and even violent offending (Domes, Mense, Vohs, & Habermeyer, 2013).

However, the negativity bias represents only one side of the affect-attention coin. In contrast to the negativity bias, the positivity offset is a lesser known, but equally relevant phenomenon that is often used to describe neutral information being attributed a subtle positivity, resulting in people’s default emotional states being both slightly positive and stable over time (Boucher & Osgood, 1969; Cacioppo, Gardner, & Berntson, 1997). Moreover, the positivity offset was found to be universal, applicable across nations and cultures, even for individuals living in very difficult circumstances (Diener, Kanazawa, Suh,

& Oishi, 2015). Further evidence for the positivity offset was found in social psychology, where it was demonstrated that observing a neutral stimulus more frequently increases the level of liking of the stimulus (e.g. even when stimulus is a nonsense word) (Zajonc, 1968). Further, positive words were found to be used more frequently than negative words in everyday language (Boucher & Osgood, 1969), providing support for the positivity offset.

Importantly, the positivity offset emerges at times of lower-intensity stimuli, e.g., people tend to feel mildly positive (rather than neutral) when no strongly emotional events are occurring. This slight lean towards positivity at times of low threat is seen as an evolutionary adaptation that underpins engagement in exploratory and approach behaviours, which can in turn increase adaptive behaviour such as creativity and sociability (Diener et al., 2015). Indeed, the positivity offset tends to fade away when stronger stimuli appear in the environment, especially if they are aversive as stronger stimuli are more likely to activate the aversive evaluation system and lead to avoidance behaviours. More recently, in their research on loss aversion – a well-evidenced phenomena regarding people generally weighing losses more heavily than gains (a parallel with negativity bias) - Harinck et al. (2007) found a reverse pattern existed in the case of small monetary outcomes, at which point gains actually loomed larger than losses (Harinck, Van Dijk, Van Beest, & Mersmann, 2007). For example, imagining they gained one euro by either finding or winning it had led to a higher self-reported happiness increase in their participant sample, as opposed to the self-reported levels of unhappiness felt when they imagined losing the same monetary amount. In their second study, Harnick et al. (2007) also found evidence for the typical loss aversion outcome appearing when larger amounts of money, e.g., 50 euros, were imagined as gained or lost. Harnick et al. (2007) concluded that loss aversion can be in fact be reversed, rather than only diminished, but only when it occurs at the lower stimuli level – a finding which supports the underlying positivity offset concept (Harinck et al., 2007).

In summary, the asymmetry of the negativity bias and the positivity offset remains dependent on both intensity and frequency of stimuli in the environment, i.e., while negativity will dominate positivity in its intensity, positivity will dominate negativity in its frequency, despite being lower in intensity. Based on this finding, it has been suggested that having positive to negative affect ratios nearing 1:1 is unlikely to signify optimal mental health, given the affective asymmetry implies more frequent positive events are necessary to counteract the negative effects of a single aversive event (Fredrickson, 2013b).

The positivity offset and the negativity bias are both part of the Evaluative Space Model (ESM) theoretical framework (Cacioppo et al., 1997; Cacioppo, Gardner, & Berntson, 1999; Norris, Gollan, Berntson, & Cacioppo, 2010). The ESM postulates that positive and negative affective dimensions are independent (rather than being polar opposites of the same continuum), and that they jointly underpin two distinct behavioural activation functions - approach or avoidance behaviours - which act separately for both positivity and negativity. While the 'appetitive, approach or incentive' motivational system has been suggested to predominantly organise behaviour involved in approaching desired goals (rewards), the 'aversive, avoidance or withdrawal' motivational system is predominantly indicated in behaviour involved in avoiding threats (punishments) (Norris et al., 2010). Overall, the activation function for positivity results in individuals experiencing higher positive than negative affect at lower levels of affective input (i.e., the positivity offset), while the activation function for negativity manifests in individuals having stronger responses to negative as opposed to equally strong positive stimuli (i.e., the negativity bias). In other words, running away from a predator would be evaluated as more momentarily important than finding a mate, although both may elicit equally strong, albeit opposite, affective responses (Norris, Larsen, Crawford, & Cacioppo, 2011).

The ESM proposes that negativity bias occurs when, all else being equal, strongly aversive stimuli elicit more intense responses than approach stimuli and that a positivity offset occurs when input to the affect system is absent or minimal, at which time positivity outweighs negativity in frequency (Norris et al., 2010). These affective asymmetries are also thought to provide evolutionary support to individuals' engaging in explorative behaviour at times of low threat, due to the overall effects of the positivity offset, while also being able to simultaneously maintain vigilance and ability to respond quickly if a potentially harmful stimuli appears, as influenced by the negativity bias (Norris et al., 2011). The ESM also suggests that approach or avoidance behaviours are the ultimate output of the complex affective system, resulting from two separate positivity and negativity systems that are each described by their unique operating features (Cacioppo et al., 1997; Cacioppo et al., 1999).

The empirical research in the ESM field has demonstrated there are individual differences in the positivity offset and negativity bias, are largely independent of each other and have important implications (Norris et al., 2011). For example, evidence for both affective phenomena can be found even at the basic biological spinal reflexes level – e.g. the fast action of flexor withdrawal reflexes is thought to be reflective of the negativity bias, are first to emerge developmentally, and the most powerful of spinal reflexes (Berntson & Cacioppo, 2008). In contrast, at times of lower environmental stimuli, research suggests that the flexor extensor activation becomes the dominant spinal reflex force, indicating an activation of the approach response, as compatible with the positivity offset (Berntson & Cacioppo, 2008). It would also appear that, at low levels of stimuli input, life generally feels mildly positive rather than neutral. In their pioneering research article "Most people are happy", Diener and Diener (1996) have demonstrated that most people around the world report positive (rather than neutral) levels of subjective well-being, therefore suggesting that normative human experience involves a basal level of positive, rather than neutral affect.

Furthermore, research has subsequently suggested a subjective well-being "set point" might exist for each individual, as evidenced by most individuals having a slightly positive default emotional state (Diener & Diener, 1996; Diener et al., 2015), and considering that following a highly positive or a highly negative event, individuals tend to eventually return to their previous (basal) levels of happiness (Brickman & Campbell, 1971; Brickman, Coates, & Janoff-Bulman, 1978). The research evidence for the happiness set-point theory will be further discussed in the section related to positive affect and its stability over time.

Emotions and Behaviour

It is evident that human behaviour is influenced by emotions, both pleasant and unpleasant. The direct role of emotion in determining human behaviour has been of particular research interest in areas of consumer psychology, e.g., with regards to how emotions influence purchase behaviours (Hansen, 2010; Penz & Hogg, 2011; Soscia, 2013; Watson & Spence, 2007; Wyer, Dong, Huang, Huang, & Wan, 2019) and in health psychology, where emotions are powerful motivators underlying dietary choices, cigarette smoking, alcohol and drug use behaviours (Aguiar-Bloemer & Diez-Garcia, 2018; Ashurst et al., 2018; Ekkekakis, 2013; Wang, Chen, Gong, & Yan, 2016; White, Horwath, & Conner, 2013). Similarly, in sport psychology, emotions are increasingly seen as an important influence on athletic performance (Cohen, Tenenbaum, & English, 2006; Robazza, Bortoli, & Nougier, 1999; Vast, Young, & Thomas, 2010; Woodman et al., 2009), whilst in organisational psychology, the understanding and managing emotions in self and others are emerging relevant factors for leadership success and organisational output (Humphrey, 2015; Nai-Wen, Ta-Rui, Lindebaum, & Jordan, 2014; Sadri, Weber, & Gentry, 2011).

However, an important issue to consider when evaluating research on emotion and behaviour is the diversity of terminology used to describe the variety of affective phenomena. For example, in the general literature on emotions (Berkowitz, 2000), affect is the broadest term that can include emotions, moods and feelings. Moods are often described as the more enduring, general emotional states that are not always consciously available, while emotions are defined as brief and target-specific affective reaction that include conscious awareness about emotion's antecedents and consequences, as well as physiological and behavioural aspects. Additionally, feelings refer to temporary, subjective and conscious aspects of emotional states which may not have a clear object (Berkowitz, 2000).

Emotions and Offending Behaviour

How do emotions relate to offending behaviour? In the field of criminology, the potential influence of emotions on offending behaviour has not been a strong focus of academic research. Similarly, the focus of psychological interventions in forensic settings has predominately been on changing individuals' cognitions, such as their antisocial attitudes or cognitive distortions. It has also been noted that, while the experiences of negative emotions are often viewed as a problem to be addressed or at least indicating a need for treatment in the general population, the presence of high levels of emotional distress in an convicted offender will not necessarily lead to a referral for psychological treatment. This is despite the fact that a high proportion of offenders worldwide meet the criteria for a mental health diagnosis (Fazel & Danesh, 2002). The lack of focus on emotions in offending and recidivism could be considered surprising given that emotions serve to integrate and motivate action, and can have a profound influence on the perception of our environment (Ward & Nee, 2009). It has previously been argued that this omission of emotion assessment and treatment in individuals who offend may in part reflect an implicit or explicit belief that negative emotions or psychological distress should be welcomed rather than treated, because individuals with offending histories deserve to be punished for their actions (Day, 2009; Hogue & Peebles, 1997).

Despite a relative lack of attention being paid to emotions of individuals who offend, there has been some growth in this research area in recent decades. For example, Tibbets (2003) examined the relationship between negative emotions of shame and guilt, and the positive emotion of pride, with offending behaviours. Regardless of their valence differences, shame, guilt and pride are all considered to be ‘self-conscious’ emotions, which are differentiated from other emotions by the requirement of self-consciousness that is not needed for many primary emotions such as joy or disgust. Self-conscious emotions are thought to arise from social interactions where people evaluate themselves and each other (Tibbetts, 2003). In his study on 224 university students, Tibbetts (2003) showed that self-conscious emotions were important in the aetiology of offending; in particular, pride was found to be positively correlated with self-reported criminal activity, whereas higher ratings of guilt were negatively associated with offending. However, the relationship between shame and offending was found to be varied across different research studies depending on the type of measure that was used to indicate proneness to shame, such that individuals with higher trait-based shame were more likely to exhibit maladaptive behaviours, whilst having higher state-base shame was found to either constrain or have a neutral effect on offending in the absence of chronic shame. An acknowledged disadvantage of Tibbetts’ (2003) study included research being conducted on a sample of university students, which contained individuals who committed offences such as driving under influence, cannabis possession and theft; as such, the sample did not contain serious offenders.

The negative emotion of shame has been of interest and discussed as part of Braithwaite’s (1989) Reintegrative Shaming theory of crime. Shame can be defined as a negative emotion arising from the imagined or real disapproval of others, and is generally felt about the self as a whole. This definition is in contrast to the feeling of guilt, which is a similarly negative feeling that tends to arise when one disapproves of one’s own behaviour, and is commonly felt about a specific action or an omission of action one has committed rather than about one's whole self (Harris, Walgrave, & Braithwaite, 2004). In his reintegrative shaming theory, Braithwaite proposed that the justice processes should focus on reintegrating the offending individuals into pro-social behaviour within their community using *informal* rather than *formal* social controls. In other words, he argued for moving away from traditional formal justice procedures which are more repressive (e.g., focused on punishment, incarceration) and leading to further stigmatisation and coerced compliance, and moving towards more informal social controls based on moralising, which would be enforced through public shaming and ideally lead to stimulation of freely chosen compliance. Braithwaite (1989) further defined shaming as the public expression of disapproval of an act, and suggested there are two main types of public shaming used by communities to stimulate behavioural change, specifically reintegrative and disintegrative shaming. While disintegrative (stigmatising) shaming refers to a public condemnation of both the individual and the act, often resulting in individual being ostracized from their community, reintegrative (non-stigmatising) shaming is defined as a public condemnation of the act, whilst retaining support for the essential goodness of the individual and support for strengthening their ties with the community (Braithwaite, 1989). Braithwaite (1989) further suggested that disintegrative shaming may in fact be complicit in strengthening of criminogenic processes, e.g., by individuals developing a pro-criminal identity through labelling, furthering of belonging to an anti-social subculture, weakening of pro-social and familial bonds through incarceration, reducing opportunities to pursue valued goals, etc. In summary, within the reintegrative shaming theory of crime, the emotion of shame felt by an individual following sanctions was postulated as central to either a development of their motivation towards desistance, or for the potential entrenching of a pro-criminal identity, depending on the way in which shame was both induced and managed by the community surrounding the offending individual. Restorative justice procedures were subsequently developed internationally as a way to provide an environment for reintegrative shaming, with promoters hypothesising that the diversion of criminal procedures to restorative justice conferences would be more effective in lowering the rate of reoffending than the traditional prosecution, as conferences more effectively engage the psychological mechanisms of reintegrative shaming and procedural justice (Tyler, Sherman, Strang, Barnes, & Woods, 2007).

However, the empirical research related to the reintegrative shaming theory has been mixed in terms of linking the non-stigmatising shaming of restorative justice conferences, and the induced shame, with reduced recidivism. A significant body of research has examined how shame manifests in restorative justice conferences (Harris et al., 2004; Morris & Maxwell, 2001; Sherman, Strang, Barnes, et al., 2015; Sherman, Strang, Mayo-Wilson, Woods, & Ariel, 2015; Strang & Braithwaite, 2000), with inconclusive evidence that there is a link between shaming, manifestation of shame, and reduced recidivism. Several limitations could have contributed to this, such as the empirical research being more focused on the sanctioning process itself as opposed to how it had affected the individuals being sanctioned (Hipple, Gruenewald, & McGarrell, 2014, 2015; McCold, 2003), giving little consideration to how individual criminogenic factors could be mediating the relationship between sanctioning and recidivism. Another issue is related to the theory's inherent assumption that the court environments are stigmatising, while restorative justice conferences were integrative (Braithwaite & Mugford, 1994), with empirical research suggesting this may not always be the case (Harris, 2006). It would therefore appear that, despite there being an appetite for restorative justice procedures being conduits for inducing reintegrative shame in offenders as a way to reduce their recidivism, research is showing that the emotion of shame is not a simple construct, and that further work is needed to better understand its nuances and potential influence on recidivism risk.

The one emotion most commonly linked with offending, and violent offending in particular, is anger, alongside its extended modifications of rage, hate and revenge. Although anger is neither sufficient nor necessary for violent behaviour, it is incorporated within a number of risk factors related to violent behaviour (e.g., negative emotionality is an element of antisocial personality pattern within the Central Eight) and can be understood as a dynamic risk factor and a treatment need for violence (Novaco, 2011). Anger has been defined as

> "a negatively toned emotion, subjectively experienced as an aroused state of antagonism toward someone or something perceived to be the source of an aversive event. It is triggered or provoked situationally by events that are perceived to constitute deliberate harm-doing by an instigator toward oneself or toward those to whom one is endeared. Provocations usually take the form of insults, unfair treatments, or intended thwarting. Anger is prototypically experienced as a justified response to some 'wrong' that has been done. While anger is situationally triggered by acute, proximal occurrences, it is shaped and facilitated contextually by conditions affecting the cognitive, arousal, and behavioural systems that comprise anger reactions. Anger activation is centrally linked to threat perceptions and survival responding" (Novaco, 2000, pp. 170-174).

Although the definition of anger provides researchers with a certain amount of clarity, in clinical practice anger is harder to extrapolate clearly because it is often experienced alongside other negative emotions such as shame, disappointment, sadness or fear (Novaco, 2011).

Within forensic contexts, the link between anger and aggression has been empirically studied across varied settings, e.g., with violent offenders in institutions (prisoners or forensic patients) and within community settings (offenders on probation or discharged patients). Forensic research findings have commonly shown anger to be an activator of aggressive behaviour in offenders (Novaco, 2011). For example, experience of anger has been found to be predictive of offenders' physical aggression prior to hospital admission (Craig, 1982; McNiel, Eisner, & Binder, 2003; Novaco, 1994), during institutionalisation (Doyle & Dolan, 2006a; Novaco, 1994; Wang & Diamond, 1999), and following discharge into community (Doyle & Dolan, 2006b; Skeem et al., 2006). For example, patient-rated and staff-rated anger was found to be predictive of physical violence in forensic hospitals, even after controlling for age, gender, length of hospitalisation, and major mental disorder (Doyle & Dolan, 2006a). Daffern et al.'s (2005) study of forensic psychiatric patients in a community forensic hospital indicated that aggressive behaviour is a function of a wide range of individual characteristics, including long-term history of aggression, recent histories of substance abuse and aggressive behaviour, as well as psychotic symptoms including hallucinations, conceptual disorganisation and thought disturbance. Somewhat contrary to other research, Daffern et al. (2005) found that anger was not significantly associated with aggressive behaviour. However, it was suggested that this discrepancy could also be due to a trait anger measure being used in their study, rather than a state anger measure (Daffern, Howells, Ogloff, & Lee, 2005). Within a prison hospital study, anger was found to be the strongest predictor of institutional aggression, even after controlling for current violent offence, personality measures and background (Wang & Diamond, 1999). Related to aggression prior to hospitalisation, McNeil et al. (2003) found that patients' self-reported anger was the strongest retrospective predictor of their violent behaviour, even after controlling for substance-related disorder, age, depression, bipolar disorder and schizophrenia. Anger has further been implicated as important in understanding the drivers of intimate partner violence, with a meta-analysis showing that anger was moderately elevated among intimate partner violent (IPV) men and particularly those who fall within the more severe IPV subtypes (Norlander & Eckhardt, 2005).

Anger and other negative emotions have also been identified as important drives in sexual offending, where a general research consensus exists that men who have sexually offended are characterised by negative affective states (Langton & Marshall, 2000; Marshall, Cripps, Anderson, & Cortoni, 1999; Smallbone & Dadds, 2000; Ward & Hudson, 2000), specifically anger and social anxiety (Gillespie, Mitchell, Fisher, & Beech, 2012). In a study of sexual offenders on community supervision order, results showed that individuals experienced an increase in general psychiatric symptoms, negative emotion and anger just before offending (Hanson & Harris, 2000). Interestingly, research into sexual offending has also discovered that experiences of positive emotions, and efforts to maintain them, may also contribute to both sexual and violent offending (Day, 2009). For example, Hudson, Ward and McCormack (1999) found that a similar proportion of sex offenders reported positive affect (37%) as they reported negative affect (44%) in the offence process for their most recent typical offence (Hudson, Ward, & McCormack, 1999). Additionally, examples of positive affect have been highlighted for impulsive or serial rapists who experience a post-offense rise in positive emotions, and for offenders who plan their offending carefully with the explicit aim of increasing or maintaining a level of generally positive affect (Ward, Hudson, & Keenan, 1998). Similarly, for instances of instrumental offending which are inherently premeditated and driven by an external goal, it was found that negative emotional states do not necessarily precede nor trigger the instrumental offending (Woodworth & Porter, 2002).

What could be the general mechanism that links emotions and offending behaviour? Agnew's (1992, 2001, 2013) strain theory of criminality postulates that individuals experiencing strains or stressors have an increased likelihood of also experiencing negative affective states such as anger and frustration. These emotions create pressure for corrective action, and criminal activity is one possible way to reduce or escape from strains (Agnew, 1992). Agnew's strain theory focuses predominantly on the strains resulting from having negative relationships with significant others, which are defined as relationships in which others are not treating the individual as he or she would like to be treated. Three major types of strain related to negative relationship with others were defined as following: i) when others prevent one from achieving positively valued goals; ii) when others remove (or threaten to remove) positively valued stimuli that one possesses, or (iii) when others present or threaten to present one with noxious or negatively valued stimuli (Agnew, 1992). Agnew also reported that certain strains may be more conducive to some emotions than to others. For example, anger may be more likely to arise when strain is seen as unjust, frustration may be more likely to arise when strain involves an inability to achieve desired goals, strains perceived as uncontrollable may lead to depressive affect, while uncontrollable and impending threats may be more strongly linked to fear (Agnew, 2013).

Agnew also argued that strains which were seen as unjust, high in magnitude, associated with low social control and which posed an incentive to engage in crime, were more likely to lead to offending behaviour (Agnew, 2001). Generally speaking, the tendency to perceive injustice in relationship with others, or to generally interpret the actions of other as hostile, has first been noted as a characteristic of individuals who engage in life-course persistent offending (Moffitt, 1993). The tendency among individuals who offend towards making hostile interpretations of neutral stimuli has been supported by research using the Massachusetts Youth Screening Instrument, Version 2 (MAYSI-II) measure of angry-irritableness (Hoeve et al., 2015) in youth offender case studies (Piquero & Sealock, 2000) and via a combined measure of frustration tolerance and hostile attribution (Baglivio, Wolff, Piquero, & Epps, 2015). Following on from this, it was suggested that criminal behaviour is more likely in individuals who perceive the actions of others as hostile and therefore unjust, leading them to resort to violent corrective action (Wolff & Baglivio, 2017). Similarly, the emotion of anger has particular importance within Agnew's General Strain theory of offending, due to the ability of anger to energise the individual for action, create a desire for revenge, diminish the individual's ability to cope legally or negotiate with others, and provide a justification for the crime, e.g., to right a perceived wrong. Feelings of anger may also further increase the ongoing perception of injustice related to the strain (Agnew, 2013).

Negative emotionality is another important factor related to general affective functioning, which has been postulated to contribute to offending. As a general construct, emotionality is considered as one of the primary components of temperament, and is defined as the ease with which emotions are aroused (Rothbart & Bates, 2006). Negative emotionality is further defined as a characteristic of individuals who interact with persons and experience their environment in a generally negative way (Clark, 2005; Delisi & Vaughn, 2014). As such, negative emotionality has been empirically found to be a significant predictor of problem behaviours, including offending (Clark, 2005; Eisenberg, Fabes, Guthrie, & Reiser, 2000; Lengua, West, & Sandler, 1998). Anger, frustration, irritability and hostility, which are considered to be 'hot' variants of negative emotionality, were linked with more externalising and anti-social behaviour problems, while anxiety and depression, which are considered to be 'cold' variants of negative emotionality, were linked with more internalising problem behaviours (Eisenberg et al., 2005; Gilliom, Shaw, Beck, Schonberg, & Lukon, 2002; Moffitt, 1993; Rothbart, 2007).

Research has also shown that individuals who offend are more likely to have experienced significant maltreatment over their lifetime than non-offenders (Evans-Chase, 2014). For example, recent research has demonstrated that children who have been exposed to one of ten possible Adverse Childhood Experiences (ACEs) - emotional, physical or sexual abuse, emotional and physical neglect, witnessing of domestic violence, household substance use, household mental illness, parent separation, and incarceration of a household member - have higher odds of poor educational and employment outcomes, substance abuse, incarceration, and recent involvement in violence (Bellis, Lowey, Leckenby, Hughes, & Harrison, 2014). Additionally, exposure to each additional type of ACE when experiencing multiple ACEs was found to increase the risk of both self-directed violence (e.g. self-harm or attempted suicide) and other-directed violence (physical fighting, bullying, weapon-carrying, intimate partner violence and delinquency) (Duke, Pettingell, McMorris, & Borowsky, 2010). However, while an increasing amount of research is linking ACEs with adverse life outcomes and an increased risk of offending behaviour, the mechanisms by which this may happen are still unclear. Negative emotionality, likely resulting from prolonged experiences to ACEs, could be implicated in this link (Wolff & Baglivio, 2017). A recent study by Wolff and Baglivio examining more than 25,000 youth offenders has shown that ACEs have both direct and indirect effect on youth recidivism, with nearly half of the total effects of ACEs on re-offending operating directly through negative emotionality (Wolff & Baglivio, 2017).

One specific theoretical model which seeks to explain recidivism as opposed to the origins of initial offending is the coping-relapse model of criminal recidivism (Zamble & Quinsey, 1997). According to this model, when individuals face an environmental trigger, which can range from chronic life stressors (e.g. financial stressor or relationship difficulties) to relatively small daily hassles (e.g. traffic jams), this could trigger the process of their recidivism into offending. Following the occurrence of an environmental trigger, each individual will make a cognitive and emotional evaluation of the situation. Individuals who perceive the situation as problematic may then experience negative emotions such as anger, hostility or fear, and a global elevation in stress levels due to feeling a lack of control over the situation. As a result, individuals may then attempt to rectify the situation, but often will lack the adequate coping skills to achieve this, leading to a worsening cycle of further negative cognitions and emotions emerging with the eventual relapse into offending behaviour. This model postulates that whether or not an individual will experience an environmental trigger or perceive the situation as problematic depends on two main factors: i) the available response mechanisms, such as coping ability, offending attitudes, anti-social network, substance use; and ii) individual influences, such as temperament and emotionality. Finally, the theory proposes that this process is ongoing and cyclical, as that each response leads to a new sequence of events resulting in another precipitating situation, new appraisals and new responses (Zamble & Quinsey, 1997).

Negative Affect and Change Over Time

Research has repeatedly demonstrated that negative affect shows significant changes over time and the life course. For example, a wide body of research in general populations has revealed a decrease in average levels of negative affect over lifetime, from early to late adulthood in general populations of men and women across countries and cultures (Charles, Reynolds, & Gatz, 2001), with older adults reporting experiencing negative affect less frequently than younger adults (Basevitz, Pushkar, Chaikelson, Conway, & Dalton, 2008; Carstensen, Pasupathi, Mayr, & Nesselroade, 2000; Mroczek & Kolarz, 1998; Phillips, Henry, Hosie, & Milne, 2008). Among several explanations for the reduction in negative affect across the lifespan, the socio-emotional selectivity theory suggests that older adults tend to increasingly prioritize emotionally fulfilling goals due to an growing perception of a reduced life-span over time (Carstensen, 2006). Further, studies indicate that older age is related to more benign cognitive appraisals of negative stimuli (Charles & Carstensen, 2010). Older adults also have more leisure time to engage in positive experiences of their choice (Ginn & Fast, 2006), likely benefit from an age –related reductions in the frequency of daily stressors (Charles et al., 2010), and report decreased reactivity to daily stressors (Birditt & Fingerman, 2003; Birditt, Fingerman, & Almeida, 2005). Although the majority of lifespan-based research involves cross-sectional studies of adults across different age groups, long-term longitudinal studies following cohorts of adults over decades are also being employed, in order to provide further contributions to understanding of negative affect changes across lifetime per each individual.

In relation to dynamic change in negative affect over shorter amounts of time (e.g. daily or weekly), the Experience Sampling Method (ESM) has emerged as an ecologically-valid research technique that has become more commonly used for studying time-based changes within individuals and groups of individuals (Delespaul, 1995; Hektner, Schmidt, & Csikszentmihalyi, 2007; Shiffman, Stone, & Hufford, 2008; Stone & Shiffman, 1994). In ESM studies, participants are asked to report their thoughts, feelings and symptoms during their normal daily life as well as context (e.g., their location, activity). ESM questions can be open-ended, categorical, or Likert-type scale questions, and are generally answered several times a day, during several consecutive days at random unpredictable moments (Myin-Germeys et al., 2009). The simplest ESM techniques used a daily diary; however, with the progress of technology, various software packages have been developed for running studies on mobile phones (Granholm, Loh, & Swendsen, 2008; Kimhy et al., 2006), providing equivalent results to diary techniques (Gwaltney, Shields, & Shiffman, 2008). The main disadvantages of using ESM include the procedure being time-consuming and perhaps intrusive and demanding for participants, as well as the possibility of a reduced adherence to the research protocol due to the absence of a researcher during completion of measure. However, the advantages of using the ESM technology include improved ecological validity of measured constructs, the reduced vulnerability to recall biases, and investigation of patterns over time due to multiple assessments (Myin-Germeys et al., 2009).

When examining the pattern of negative affect change in everyday life, ESM research often includes assessing individuals' responses to minor daily stressors in everyday life. Such ESM studies have repeatedly shown that significant increases in negative affect, as well as a general decrease in positive affect, are associated with minor stressful daily events both in non-clinical samples (Jacobs et al., 2007; van Eck, Nicolson, & Berkhof, 1998), as well as in clinical samples of individuals diagnosed with depression, anxiety or psychosis (Bylsma, Taylor-Clift, & Rottenberg, 2011; Myin-Germeys, Krabbendam, Delespaul, & Van Os, 2003; Peeters, Nicolson, Berkhof, Delespaul, & deVries, 2003; Wichers et al., 2007). An increased negative affect in response to daily stressors was also found to be a risk factor for developing depression (Mezulis et al., 2010; Siegrist, 2008), while individuals with affective disorders such as anxiety and depression were reported to consistently experience higher levels of negative affect in their daily lives (Watson, Clark, & Stasik, 2011). The ESM evidence thus points to a link between higher negative reactivity to daily stressors and the development of affective disorders.

One potential reason behind higher negative reactivity to daily stressors was explored in an ESM-based study of the relationship between childhood trauma (characterised as experiences of sexual or physical trauma before the age of 19) and emotional reactivity to daily life stressors. The results showed that individuals with childhood trauma history reported significantly higher increases in negative affect when daily stressors occurred, compared to individuals with no significant history of childhood trauma. Furthermore, this finding was most pronounced for individuals who had experienced childhood trauma earlier in life (before aged 10 years), suggesting that the trauma-related effects on ability to regulate negative affect are more detrimental when trauma occurs at a younger age (Glaser, van Os, Portegijs, & Myin-Germeys, 2006). As previously mentioned, criminology research has also shown that individuals who offend are more likely to have experienced significant maltreatment over their lifetime than non-offenders (Evans-Chase, 2014), due to exposure to a list of ten Adverse Childhood Experiences (ACEs) (Bellis et al., 2014). Negative emotionality, a characteristic of individuals who interact with persons and experience their environment in a generally negative way (Clark, 2005; Delisi & Vaughn, 2014) has been empirically found to be a significant predictor of problem behaviours, including offending (Clark, 2005; Eisenberg et al., 2000; Lengua et al., 1998; Rothbart & Bates, 1998).

Another potential reason for the higher daily negative affect fluctuations occurring as a result of minor daily stressors in both clinical and non-clinical populations is the previously discussed negativity bias, which refers to an evolutionary driven heightened sensitivity towards negatively valanced information which is present at different levels of cognitive processing (Baumeister et al., 2001). In other words, human attention is more easily captured by aversive or threatening events, even if these are minor daily hassles, which can lead to higher corresponding spikes in negative affect across the day. Previous studies have found that negativity bias has a significant relationship to psychological functioning over the lifetime, particularly related to depression and anxiety (Bar-Haim et al., 2007; Gollan et al., 2016; Koster et al., 2009; Macleod et al., 1986). Individual levels of emotional reactivity towards a daily stressor would depend on a multitude of factors, inclusive but not limited to levels of childhood trauma, negative emotionality, presence or absence of mental illness, current or past substance abuse, general health, age, and overall life circumstances. Notably, individuals who engage in offending behaviours are also more likely to have experienced childhood trauma, mental illness or significant substance abuse, all of which have been identified as risk factors for increased emotional reactivity to daily stressors.

Emotions and Desisting Behaviour

Examining the specific role of emotions in desistance processes has been a relatively novel area in criminology research. In particular, de Haan and Loader (2002) highlighted that emotions have long remained a peripheral topic in most major criminology theories, and called for "criminological theorising to take more serious account of the affective dimensions of criminal behaviour" (De Haan & Loader, 2002, p. 245). Considering the general paucity of research on emotions in general criminology, it is not surprising that even less attention has been paid to research on emotions and desistance, with only a few existing studies of desistance examining the significance and role of emotions in change from offending to desisting (Robinson & Hamilton, 2016).

In terms of how emotions may fit into the main theories of desistance, Maruna (2001) identified that desisters are able to acquire new identity scripts ('redemption script'), although he did not explicitly consider how individuals' emotional states could be involved in shaping this process. Similarly, Giordano, Cernkovich & Rudolph (2002) proposed a new symbolic-interactionist perspective to challenge the informal social control theory of crime which was outlined by Sampson and Laub (1993). Giordano et al. (2002) highlighted the important role of agent-based changes in desistance, in addition to the importance of external influences on offenders' behaviour which were highlighted by Sampson and Laub (1993). It was suggested that future research is required to "add attention to emotions as they affect behavioural change directly or, indirectly, as they influence the nature and timing of cognitive shifts" (Giordano, Cernkovich, & Rudolph, 2002, p. 1055). Following this, in a 2007 follow-up study, Giordano and colleagues revised their symbolic-interactionist theory towards also considering the specific role of emotions and individuals' emotional selves in the desistance process. Their follow-up study showed that three emotion-specific life-course changes can have a direct effect on desistance: (i) the reduction of negative emotions originally connected to crime, (ii) the decrease of positive emotions, and (iii) increased skill in emotion regulation or management. Regarding the reduction in negative emotions originally connected to crime, Giordano et al. (2007) postulated that as young people mature into adulthood and experience role-taking opportunities, the original emotions which may have connected them to offending behaviour (e.g. anger) will diminish, thus diminishing their offending. Regarding the decrease in positive emotions, they further postulated that a move into adulthood facilitates a reduction in positive emotions associated with crime, such as pride. Finally, the authors argued that their quantitative study data had lent support to the notion that their participants showed an increased ability over time to regulate or manage their emotions in a socially acceptable way. Overall, the authors argued that 'emotional mellowing' may be associated with important life-course transitions (e.g. entering employment and marriage), but also that it can occur as part of emotional development of the person and not necessarily be linked with an obvious catalyst or a life transition (Giordano et al., 2007).

Negative emotions have been further implicated as an important factor in continued re-offending, with 'anger identity' being found to significantly reduce the odds of being a stable desister in both general but also in violent offending (Giordano et al., 2007). Feelings of being 'doomed' due to a social stigma of being ex-offender, reported just before their release from prison, were found to predict both reconviction and re-imprisonment, even after controlling for a number of social problems experienced post-release (Lebel, Burnett, Maruna, & Bushway, 2008).

Conversely, maintaining desistance has been linked with feeling positive rather than negative, with ex-offenders reporting feelings of pride at having desisted, satisfaction with their lives or the pleasure derived from prosocial roles such as parenthood**,** albeit from a point in time significantly removed from their criminal history, when stable desistance has been achieved (Farrall, Hunter, Sharpe, & Calverley, 2014). It has been suggested that the transition period or a pathway from offending to stable desistance is more likely to be laced with emotional ambivalence, as evidenced in a 'zig zag' pattern of individuals having crime-free periods punctuated with re-offending (Baker, Metcalfe, & Piquero, 2015). For example, feelings of regret for one's past involvement in crime and a positive self-identification as a 'family man' both seem to contribute positively to the desistance process, despite their different emotional valence (Lebel et al., 2008). It was therefore suggested that it is necessary to consider in more detail when the positive feelings associated with avoiding offending occur and, more specifically, whether avoiding offending feels good at the time (Hunter & Farrall, 2018). A new branch of psychology, which is focused on understanding and improving experiences of positive emotions, may be well positioned to inform and provide relevant scaffolding for further exploration of positive emotion experiences in relation to offenders. The next section will explore areas of Positive Psychology research, its focus on positive emotions and their link to behaviour.

Positive Psychology and Positive Emotions

Positive psychology is a relatively new branch of psychology that is less concerned with trying to understand what is going wrong, and more concerned with understanding how to improve and maximise mental wellbeing for a satisfactory life (Waters, 2011). Historically, psychology has focused on identifying effective approaches to addressing mental health difficulties, and, consequently, positive mental health or flourishing has not been the predominant focus of psychological research. Positive psychology aims to address this gap as it is the "study of conditions and processes that contribute to the flourishing or optimal functioning of people, groups and institutions" (Gable & Haidt, 2005, p. 103). It includes assessments and interventions that are aimed at improving social-emotional learning, increasing life satisfaction, promoting learning, and improving social cohesion while protecting against mental health issues (Kern, Waters, Adler, & White, 2015). Positive psychology interventions in particular are designed with an aim to cultivate positive emotions, cognitions and behaviour as a way of assisting the effective traditional methods in improving adverse mental health, as well as to increase a sense of flourishing for those without serious mental health problems (Seligman & Csikszentmihalyi, 2014).

With regards to general affective states, research on the basic architecture of emotions has found two reliable dimensions: positive and negative affect (Vazquez, 2017). These two dimensions have been consistently identified across diverse cultures, languages and time

(Russell, 1980; Watson & Tellegen, 1985). Whilst the negative affect is a general dimension of emotional distress that includes a variety of specific negative emotional states (e.g., sadness, anger, hopelessness, etc.), the positive affect dimension includes several positive emotional states (e.g., alertness, happiness, enthusiasm). Importantly, research has demonstrated that these two dimensions are independent rather than being the polar opposites of the same continuum, and that they often can co-occur (Watson, 2005). Experienced and expressed positive emotions in particular have been found to predict quality of life (Diener, Suh, Lucas, & Smith, 1999; Harker & Keltner, 2001), but also life quantity (Danner, Snowdon, & Friesen, 2001; Moskowitz, Epel, & Acree, 2008; Ostir, Markides, Black, & Goodwin, 2000). Thus far, research has also shown that induced positive affect has a wide variety of benefits including widening the scope of attention (Fredrickson & Branigan, 2005; Rowe et al., 2007), broadening behavioural repertoires (Fredrickson & Branigan, 2005), increasing intuition (Bolte et al., 2003) and creativity (Isen et al., 1987). Characteristics related to positive affect also include confidence, self-efficacy and optimism; sociability, activity and energy; prosocial behaviour; immunity and physical well-being, originality and cognitive flexibility – all of which encourage active involvement with goal pursuits (Lyubomirsky, King, & Diener, 2005).

A pioneer advocate for the hidden utility of positive emotions, Fredrickson (1998) argued that positive emotions have a functional value beyond merely feeling pleasant by facilitating and building social connections and relationships. As part of Fredrickson's broaden-and-build theory, negative emotions are thought to narrow an individual's range of thoughts and actions, focusing their resources on survival, 'fight' and 'flight' behaviours (Fredrickson & Levenson, 1998). In contrast, experiences of positive emotions were postulated to momentarily broaden individual's mindset, including available problem-solving thoughts and actions ("play" and "explore"), and by doing so to facilitate generativity and behavioural flexibility (Fredrickson, 2001, 2003). Moreover, Fredrickson argued that this can create upward spirals of positive emotions, cognitions and actions, allowing for personal development and transformation.

Positive emotions in particular seem to be conduits to improving interpersonal relationships by promoting cognitive and affective expansion towards considering others. For example, in their study of first year college students developing relationships with their new roommates, Waugh and Fredrickson (2006) discovered that there is a link between positive emotions and self-other overlap. They found that self-other overlap predicted a more complex understanding of one's new roommate over time, creating a deeper interpersonal bond (Waugh & Fredrickson, 2006). This finding had also provided support for self-expansion theory (Aron & Aron, 1997), where it was hypothesized that one way in which positive emotions broaden people's mindsets is to expand their sense of self to include close others to a greater degree.

Positive Emotions and Behaviour

What are the mechanisms that may underlie positive emotions influencing behaviour? In a neuropsychological theory of positive affect and its influence on cognition, Ashby et al (1999) postulated that positive affect influences cognition through the dopamine system, which was found to be heavily involved in the neurobiology of reward (Beninger, 1983; Liebeman & Cooper, 1989; Wise & Rompre, 1989). Ashby et al. suggested that reward often induces positive affect in humans (e.g., after receiving an unanticipated gift, which is the most common reward condition in experiments), and so it is possible that many of the behavioural influences of positive affect are mediated by the same neural pathways that also mediate reward, i.e. the dopamine system. Ashby et al (1999) further assumed that positive affect is associated with increased levels of dopamine in the brain, but they did not assume that dopamine directly causes the pleasant feelings associated with positive affect. However, they postulated that increased dopamine levels in the brain will be associated with at least some changes in cognitive processing, which is supported by the previously discussed research that show facilitating effects of positive affect on problem solving, improved social interaction, and a host of other cognitive tasks such as olfactory memory, episodic memory, working memory, and creative problem solving. Ashby et al.'s (1999) theory also does not assume that positive affect simply turns dopamine on or off. Instead, it was hypothesized that moderate levels of dopamine are present even under neutral affect conditions, and that the induction of mild positive affect is assumed to increase these normal dopamine levels slightly, and facilitate improvements on a host of cognitive tasks (Ashby, Isen, & Turken, 1999).

Vulpe and Dafinoiu (2011) explored whether the positivity ratio (positive vs negative emotions) in a group of 93 Romanian high-school students predicted their levels of irrational thinking, as well as to investigate the influence of positive emotions on adolescents' creative thinking and resistance to change. Their results demonstrated that a higher positivity ratio significantly predicted participants' having a lesser tendency towards irrational thinking, specifically for engaging in global evaluation of their personal value. They also found that, in comparison with neutral emotions, positive emotions had led to improved results related to the three dimensions of creating thinking: fluency, flexibility and originality. Furthermore, positive emotions have also reduced resistance to change, such that participants whose emotions were positively manipulated tended to resist change to a lesser extent that individuals who were subject to neutral or negative emotion induction (Vulpe & Dafinoiu, 2011). It was argued that these results have important implications for application in psychotherapy and are supportive of the Broaden and Build Theory of Positive Emotions (Fredrickson, 2001). Inducing positive emotions in therapy could improve the flexibility and originality of clients' creative thinking, leading to helping individuals more easily generate novel solutions to their problems, and to accept change more readily. Also, it was hypothesised that increasing the positivity ratio in therapy, e.g., by using positive psychology therapy approaches, could lead to reduction in client's tendency to irrationally evaluate their selves in global terms by helping them to think of their failures in specific domains without extending these globally to their personal value, which could assist in therapeutic process (Vulpe, 2010).

In a meta-analytic study on relationship between different mood states and creativity, effect sizes indicated that positive mood produced more creativity than neutral mood controls, although no significant differences on creativity were found between negative moods and neutral controls, nor positive and negative moods (Baas, De Dreu, & Nijstad, 2008). Creativity was further found to be more enhanced by the activating positive mood states such as feeling happy, as opposed to deactivating positive mood states such as feeling relaxed. With regards to negative moods and their influence on creativity, negative activating moods such as fear or anxiety were associated with lower creativity, while negative deactivating moods such as sadness were found to have no association with creativity. Overall, Baas and colleagues (2008) results showed that activating mood states, regardless of their positive or negative valence, produce more creativity than deactivating mood states, which is in contrast to popular belief that relaxation leads to novel ideas. In fact, the authors suggested that promoting activating mood states, regardless of their valence, may be more fruitful toward generating creative thinking than promoting feeling relaxed or sombre. Moreover, these results were found to be predominately generalized across different experimental and correlational designs, populations (e.g., students vs. general adult populations), and creativity domains (e.g., fluency, flexibility, originality, eureka/insight). In terms of practical implications, promoting tasks as "enjoyable and interesting to do" rather than "serious and important for your job or schooling" would help with increasing feelings of happiness and joy that bolster creative thinking in the task. Based on these research findings, it could also be argued that improvement in positive emotions and creative thinking is an important aspect of improved cognitive flexibility in problem solving, which could be particularly relevant in offenders being able to generate novel solutions to life problems.

Positive Affect and Stability Over Time

Empirical research into the average levels of positive affect suggests that it remains relatively stable within individuals and through the lifespan. A wide body of research regarding positive affect from early to late adulthood for general populations of men and women across different countries points towards its longitudinal stability (Carstensen et al., 2000; Carstensen et al., 2011; Charles et al., 2001; Gross et al., 1997), with some research reporting only a slight decrease in positive affect occurring for adults in their 60s to mid-80s (Carstensen et al., 2011; Charles et al., 2001). Researchers have postulated that the decreases in average positive affect and well-being late in life may not be related to the ageing process, rather, they could be related to a decreased distance from dying and other mechanisms predicting death, known as the terminal drop (Gerstorf, Ram, Röcke, Lindenberger, & Smith, 2008). Due to the complexities of conducting lifespan longitudinal research that includes ongoing collection of multiple variables related to physical, emotional, and social functioning, research in this area is still ongoing and inconclusive at this time.

One explanation for the stability of positive affect over time could be that there is an optimal happiness set-point for each individual, so that even highly positive life-changing events (e.g., winning the lottery) would lead to, at best, a temporary increase in positive affect, followed by a return to the same happiness set-point representing each person's baseline before the life-changing positive event. In a classic study by Brickman, Coates and Janoff-Bulman (1978) which focused on the impact of large lottery wins on individuals' happiness levels, this was cross-sectionally explored by comparing a sample of 22 major lottery winners with 22 controls and 22 paralysed accident victims. Their study results showed that, contrary to the popular expectations, lottery winners did not report being happier than the controls, and the lottery winners also took significantly less pleasure from a series of mundane life events. Furthermore, their results were not due to any significant differences between people who regularly buy lottery tickets versus those who do not, nor between interviews that made or did not make lottery winning a salient topic of discussion (Brickman et al., 1978).

To place these results into a wider context, Brickman et al (1978) linked them with the general adaptation level theory (Helson, 1964), or the idea that current happiness is relative compared to previous peak experiences, current common daily experiences and peer group experiences. The adaptation level framework suggests that two main processes - contrast and habituation – operate together to prevent a large lottery win from elevating happiness to a greater level over time. Firstly, contrast refers to the effect of experiences that are salient or extreme, and may be relevant to many other life occurrences. In the lottery win example, it was hypothesised that the thrill of winning the lottery would make many ordinary events much less pleasurable, since they would now unfavourably compare with a peak past experience, such as a lottery win. This type of contrast effect was thought to reduce the overall happiness levels past a positive peak experience.

The second limit to increased happiness following a significant positive event could arise through the process of automatic habituation, which suggests that psychological systems in general will react to both positive and negative deviations from one's current adaptation level, and are considered adaptive because they will allow for constant stimuli to fade into the background (e.g., sensory adaptation), causing only temporary fluctuations in positive or negative affect before a return to a baseline level (Helson, 1964). For a highly positive life event example, automatic habituation suggests that a lottery win is both thrilling in itself and can make new pleasures available to winners. However, over time, the initial thrill of the lottery win will wear off, and the previously novel pleasures will start to be experienced as more mundane and, therefore, less pleasurable.

The hedonic treadmill theory was further built on the automatic habituation model. In the original treadmill theory, Brickman and Campbell (1971) proposed that, if good and bad events temporarily affect happiness and people quickly adapt back to hedonic neutrality, then individual and societal efforts to increase happiness are doomed to failure. While people may continue to pursue higher levels of happiness because they believe that greater happiness lies in the next goal accomplished, they may do so without realizing that in the long run their efforts are futile due to the hedonic treadmill (Brickman & Campbell, 1971). In other words, despite the popular belief, significant positive life events do not automatically lead to a long-term increase in happiness levels. In fact, it would appear that such events ultimately do not make us any happier than before, providing argument for the existence of a stable "happiness set-point" that individuals tend to gravitate towards regardless of their more transient life circumstances.

Another potential contributing factor to the happiness set-point is the positivity offset, or the previously discussed human tendency to assign a level of subtle positivity to neutral stimuli, especially at times of low stimulus intensity in the environment (Boucher & Osgood, 1969; Cacioppo et al., 1997). When the positivity offset is coupled with the automatic habituation effects across daily lives, it could be suggested that most people likely spend the majority of their conscious daily life navigating routine environments they become largely accustomed (or habituated) to, and that for this reason their daily routines present a low stimuli environment where the positivity offset (i.e., the tendency to maintain a set level of a mildly positive affect) can occur, arguably underpinning the relatively stable existence of our personal happiness set-point. While the unexpected aversive or rewarding life events occur to interrupt our daily routine and the associated mildly positive affect, such events are also not frequent enough for most individuals to become habituated to them. Once unexpected events are finished, and individuals manage to re-establish predominantly low stimuli daily routine due to re-habituation, the positivity offset re-emerges as a response, contributing to the individual happiness set-point.

While positive affect and its stability over time remain an ongoing topic of scientific research, it has also been acknowledged that emotional life is a complex construct comprised of many combinations of positive and negative affect experiences that can occur simultaneously. One way previous positive psychology research has attempted to account for the dynamic complexity of concurrent positive and negative affect experiences was to consider their ratio.

The Positivity Ratio

Interestingly, research into the ratio of positive versus negative emotions has also provided some valuable insights into potential mechanisms driving the impact of positive emotions on behaviours and experiences, where these are often experienced in conjunction with negative emotions. For example, several studies have concluded that “bad is stronger than good” (Baumeister et al., 2001, p. 323), indicating that experiences of positive emotions need to outnumber the experiences of negative emotions in order to overcome the adverse impact of negative emotions on wellbeing.

Gottman’s (1993) early research found that a successful marriage can be predicted for couples who are able to maintain a positive to negative interpersonal affect ratio of 5:1. He and his colleagues observed 73 married couples discussing a conflict area in their relationship. They measured positivity and negativity using two coding dimensions: one focusing on the observable positive and negative emotions, the other on instances of positive and negative verbal communication. They observed that a positivity ratio of 5 for verbal communication and 4.7 for observed emotions amongst lasting marriages that both partners found satisfying. Conversely, for marriages who were heading towards dissolution, a mean positivity ratio of 0.9 was found for verbal communication and 0.7 for observed emotion (Gottman, 1993).

The reformulated state of mind model, based on the mathematical model of consciousness derived from Boolean algebra, suggested that optimal mental health is associated with higher ratios of positive to negative affect (Schwartz, 1997). In particular, it was suggested that normal functioning is characterised by positivity ratio of 2.5:1, while optimal functioning was characterised by positivity ratio of 4.3:1 (Schwartz et al., 2002). Further arguments for the importance of positivity ratio as an indicator of healthy affective functioning was found in a study of 66 men who were being treated for depression. Before treatment, the patients' positivity ratios were low at 0.5. After treatment, the positivity ratios of patients who showed optimal remission were 4.3, whereas the ratio was 2.3 amongst those showing typical remission, while 0.7 in patients who showed no remission (Schwartz et al., 2002).

Most famously, however, Fredrickson and Losada (2005) surveyed 188 participants about experienced positive and negative emotions over 28 days. Their results showed that a mean ratio of positive to negative affect was above 2.9 for individuals classified as 'flourishing', and below that threshold for those identified as 'not flourishing'. The term 'flourishing' has been described in the positive psychology field as a state of optimal mental health, in the absence of mental illness, which includes a combination of 'feeling good' (hedonic wellbeing) and ‘doing good’ (eudemonic wellbeing). Flourishing has often been contrasted with ‘languishing’ that is experienced by individuals as a result of common mental health disorders such as anxiety and depression, where individuals are likely to be feeling flat and exhibit poor functioning through low motivation, poor insight or impaired decision making (Catalino & Fredrickson, 2011; Fredrickson, 2013a, 2013b; Seligman & Csikszentmihalyi, 2014). It has been suggested that a required diagnostic criteria for ‘flourishing’ is the presence of positive emotionality, i.e., a knowingly or unknowingly cultivated abundance of positive emotions that is experienced in flourishing individuals’ day-to-day living (Keyes, 2002). Frederickson and Losada (2005) suggested that, based on their study data and the associated mathematical modelling, positive emotions do not build personal and social resources unless they are experienced within a ratio of positivity to negativity equal to or greater than 2.9 (Fredrickson & Losada, 2005), which was also subsequently referred to as the ‘critical 3-to-1’ positivity ratio. However, in the following years, the critical examinations of the calculations used to derive the suggested ‘critical 3-to-1’ flourishing ratio grew, with several other authors strongly arguing that a flawed mathematical model was used to derive Fredrickson and Losada’s (2005) critical positivity ratio conclusion (Brown, Sokal, & Friedman, 2013, 2014a, 2014b).

In particular, Brown et al. (2013) first reported finding no theoretical or empirical justification for the use of differential equations from the nonlinear dynamics modelling drawn from a subfield of physics, as utilised by Friedrickson and Losada (2005), to account for changes in human emotions over time. Brown et al. (2013) concluded that based on the incorrect application of this model, Fredrickson and Losada’s (2005) claim of their findings demonstrating the existence of a critical minimum positivity ratio of 2.9 was “entirely unfounded” (Brown et al., 2013, p. 2). The authors further warned the scientific psychological community of the need to more rigorously question future applications of differential equations to studying specific psycho-social phenomena, in order to ensure the validity of researchers' justifications for using these models appropriately, and to avoid future data misinterpretations (Brown et al., 2013).

While Losada declined to respond to this criticism, Fredrickson (2013b) indicated in her reply to Brown et al.'s (2013) criticism that it would appear that the mathematical aspects of the critical positivity ratio calculations were "now-questionable", however, that she did not have enough mathematical expertise or insight to defend them (Fredrickson, 2013b, p. 814). Fredrickson (2013b) further noted that, since the publication of the 2005 article, she had taken precautions to not present the finding of 3-to-1 critical positivity ratio as an unquestionable fact, as well as that Brown et al.'s (2013) article has spurred her to review the available positivity ratio empirical evidence up to that point. Following the review of available empirical research, Fredrickson suggested that current evidence suggests that: (i) when considering positive emotions, more is better, but only up to a point (especially in the case of self-focused positive emotions); and (ii) regarding negative emotions, less is better, also up to a point – as "negativity can either promote healthy functioning or kill it, depending on its contextual appropriateness and dosage relative to positive emotions"(Fredrickson, 2013b, p. 820). Fredrickson (2013b) concluded that, despite the mathematically invalid suggestion of 3-to-1 as being a critical positivity ratio for flourishing individuals, the empirical research still shows the utility of considering higher positivity ratios as indicators of better overall functioning, within bounds. The positivity ratio results were also in line with Frederickson's (2001) broaden-and-build theory of positive emotion, which suggests that the evolutionary function of positive emotions, which was more likely to occur in non-adverse life circumstances, was to build individual's survival resources on a more long-term scale than the negative emotions (Fredrickson, 2001, 2013b). In other words, broaden-and-build theory posits that while negative emotions (and the associated urges to fight, flight or freeze) help humans to adapt momentarily as a quick survival mechanism, positive emotions (which are more likely to occur during non-adverse times) cause moments of expanded awareness that are evolutionary useful for discovery of new long-term skills through actions such as playing, exploration, savouring and integration, which in turn help humans to broaden and build a repertoire of enduring resources for survival (Fredrickson & Levenson, 1998).

Although Brown et al (2013) have strongly asserted that the 3-to-1 critical positivity ratio tipping point is scientifically unfounded due to mistakes made in the mathematical modelling that was used to derive it, they also conceded that there is "nothing intrinsically implausible about the overall idea that people with higher positivity ratio might experience better outcomes than those with a lower ratio"(Brown et al., 2013, p. 29). Overall, the positive psychology research evidence in this field has been amounting to further support the idea that, across a wide range of ages and life circumstances, people with higher positivity ratios have better mental health and adjustment than those with lower ratios. For example, Diehl, Hay and Berg (2011) used data from a 30-day diary study with 239 adults (81 young, 81 middle-aged, and 77 older adults), to examine if a specific ratio between positive and negative affect distinguished individuals with different mental health status (e.g. flourishing versus languishing), across the adult life span. While their results had supported the hypothesis that higher positivity ratios were associated with better mental health across the lifespan, interestingly, no single critical ratio had emerged as a clear tipping point that might distinguish flourishers from others. Moreover, they found that increasing age across adulthood was also associated with an increasing preponderance of positive to negative affect, and that the variability of the positivity ratios indicating flourishing mental health was particularly large for the middle-aged and older adult participant cohorts (Diehl, Hay, & Berg, 2011). Indirectly, the results of this study were supportive of the wider research suggesting existence of affective asymmetry between positive and negative affect across the human lifespan, with research indicating positive emotions remaining relatively stable across the lifespan, while negative emotions slowly but steadily decline from early to late adulthood (Carstensen et al., 2000; Carstensen et al., 2011; Gross et al., 1997).

In their study of factors that may drive flourishing, Catalino and Fredrickson (2011) used the Day Reconstruction Method to compare details of an average Tuesday in the lives of flourishers, non-flourishers, and depressed individuals. Firstly, their results showed that flourishers tend to experience bigger boosts in positive emotionality as a response to routine daily events - such as learning, helping another person or engaging in spiritual activity - as opposed to the non-flourishing or depressed individuals (Catalino & Fredrickson, 2011). Secondly, they found that higher positive emotional reactivity in flourishers had predicted higher levels of the cognitive resource of mindfulness over time. Thirdly, no significant differences were found in relation to the degree of negative emotions that was experienced between all three groups. Overall, Catalino and Fredrickson (2011) concluded that human flourishing appears to be based on small, yet important, individual differences in positive emotional sensitivity in response to pleasant daily events. While negative emotional sensitivity seems to fuel depressive affect, a parallel process of positive emotional sensitivity may be what is fuelling flourishing mental health states (Catalino & Fredrickson, 2011). Overall, the results from this study suggested that a positivity ratio of propensity for positive emotionality over negative emotionality may again be valuable to consider for better understanding of overall human mental health, and associated behavioural patterns.

In further study by Trute et al. (2010), 195 mothers of children with intellectual and developmental disabilities were interviewed over the telephone as a way to assess the impact of each mother’s cognitive appraisal of their child’s disability, and each mother’s daily positivity ratio (as measured by the Positive and Negative Affect Schedule) on their overall family functioning. Trute et al. (2010) found that both the mother’s level of positive appraisal of the impacts of childhood disability, as well as their positivity ratio (positive versus negative PANAS affect), were jointly related to overall family adjustment. This finding has led to conclusion that the ratio of positive to negative affect remains a promising approach in the assessment of mother's overall coping resources in relation to coping with child disability, which was seen as supportive of Fredrickson (2001) broaden-and-build theory in terms of helping mothers and families to achieve better longer-term adjustment to impacts of childhood disability (Trute, Benzies, Worthington, Reddon, & Moore, 2010). Notably however, the study limitation was that the authors used only the positivity ratio scores, rather than its separate positive and negative affect scores, as they considered that the positivity ratio was an important representation of the overall emotional quality of a person's life that predicts subjective well-being, as based on the work by Fredrickson and Losada (2005). It would have been informative to know how each individual affective component of the positivity ratio may have influenced the dependent variable.

Other studies using the PANAS scale have also highlighted the potential utility of the diagnostic value of the positivity affect. For example, in relation to better health outcomes, higher positivity ratios were found to significantly predict better self-reported sleep quality for a sample of 1,172 adults aged 34-83, indicating that positive affect may serve a protective function in relation to better sleep outcomes (Imel, Schreiber, Shoji, Tighe, & Dautovich, 2017). In a study of adult lung transplant candidates' self-reported affect over time, a higher positivity ratio was associated with decreased death while waiting for the transplant, indicating that enhancing positive affect may be a useful target for psychological intervention in lung transplant candidates (Pennington et al., 2020). Similarly, in a study of African Americans with Type 2 Diabetes Mellitus, participants were classified as flourishing (positivity ratio ≥ 2.9), languishing (positivity ratio = 1.0 to < 2.9), or depressed (positivity ratio < 1.0). Given that the precise "tipping points" underlying the positivity ratio have been questioned, they conducted an additional analysis using cut scores based on the distribution of our sample. Their results showed that flourishing individuals with Type 2 Diabetes Mellitus reported significantly higher levels of resilience and minimal depressive symptoms, as opposed to the languishing Type 2 Diabetes Mellitus group, who reported experiencing more negative than positive affect and significantly lower levels of resilience. The authors concluded that their results provide support for the utility of considering positivity ratios in individuals with Type 2 Diabetes Mellitus, as well as to the Keyes' definition (Keyes, 2002) of flourishing as not a mere absence of mental illness symptoms, but also of the presence of emotional vitality and growth, even in the face of adversity (Steinhardt et al., 2015).

Research has also recently begun to address the issue of moderation effects on positivity ratio results based on different studies' methodological variations in instruments used to measure affect, as well as according to the chronological age of their participants. In particular, Shrira, Bodner and Palgi (2016) tested the relationship between flourishing and positivity ratio while accounting both for different measures of affect and different rating scale formats. They conducted multiple studies; their results from the first two studies demonstrated that positivity ratio is significantly affected by the affect scale used, such that a more valence-saturated measure (e.g., Scale of Positive and Negative Experience; SPANE) produced higher ratios than a more arousal-saturated measure (e.g., Positive and Negative Affect Scale; PANAS). Based on this result, the authors suggested that it may be best to continue using affect scales that assess both the arousal (activation) and valence dimensions of affect, and that multiple-item measures should be preferred over single-item measures of positive and negative affect. However, the positivity ratio was not affected by the rating scale format, with positivity ratios generally remaining similar regardless of whether the rating scale included 5 or 8 scale points. Their subsequent studies also showed higher positivity ratios amongst older adults, indicating the importance of considering participants' chronological age in future research as an important moderating factor related to average positivity ratios. Interestingly, positivity ratios also appeared to be unaffected by the temporal span investigated (i.e., daily, last week's, or last month's affect). Overall, Shrira et al. (2016) concluded that the positivity ratio is moderated by both methodological variants – particularly the type of affect scale used - and by the chronological age of the sample (Shrira, Bodner, & Palgi, 2016).

Dynamic Affect and Recidivism – Brown, St Amand and Zamble (2009)

The current study is a three-wave study of dynamic affect collected over the same time period with official records of recidivism, and it follows on from the pioneering research conducted by Brown, St Amand and Zamble (2009). Brown et al. (2009) employed a three-wave, prospective panel study design with a sample of 136 adult males on probation, all of whom were post-release from Canadian federal prisons. Overall, Brown et al. (2009) were interested in determining whether or not the re-assessment of prospectively-rated dynamic risk factors can improve predictive accuracy of recidivism outcomes over and above static risk. Secondly, in relation to dynamic risk predictors, they sought to examine and describe if natural patterns of change exist over time. Their comprehensive research design included a variety of independent static risk factors, such as age, recidivism risk category, psychopathy level as measured by the PCL-R (Psychopathy Checklist – Revised) (Hare, 1991), antisocial behaviour as measured by CATS-SR (Childhood and Adolescent Taxon Scale – Self-Report) (Harris, Rice, & Quinsey, 1994), and the number of prison misconducts during the 12 months prior to release. Furthermore, a wide range of dynamic risk factors were also collected on three separate occasions via various measures, e.g., the Problem Survey Checklist (PCS) was used to assess acute dynamic triggers such as: marital / family difficulties, employment difficulties, accommodation difficulties, financial difficulties, poor use of time, interpersonal conflict, as well as physical and emotional health. The Perceived Problem Index (PPI) was further utilised to measure the extent to which the individuals were worried about any of the 15 potentially criminogenic factors, whilst the Perceived Stress Scale (PSS) was used to capture the extent to which individuals find their lives unpredictable and overloaded as time on probation continued. Other dynamic variables such as substance abuse, supervision compliance, social support, coping ability, criminal associates and criminal attitudes were also collected. Most relevant to the current research, the PANAS scale was also used to capture dynamic positive and negative affect over time for their sample of adults on probation (Brown et al., 2009).

Overall, Brown et al. (2009)'s results demonstrated that a systematic re-assessment of dynamic risk factors enhanced the predictive accuracy of recidivism outcomes beyond static risk factors, with the most promising predictive models being those that incorporated both static and time-dependent dynamic information. Specifically in relation to their PANAS scale results, Brown et al. (2009) found that the overall negative (but not positive) affect: (i) demonstrated a significant pattern of dynamic change over time on probation, and (ii) was a significant dynamic predictor of participants' recidivism outcomes (Brown et al., 2009). In contrast, when they examined the PANAS positive affect, only Time 1 positive affect was found to be inversely related to recidivism outcomes for their sample of adults on probation, with the dynamic overall positive affect measured over three time points emerging as a non-significant predictor of recidivism outcomes. Brown et al (2009) further noted that positive affect had, somewhat unexpectedly, remained relatively stable over the participation time of their study (approximately three to five months), thus challenging their original hypothesis of positive affect being a dynamic variable that could contribute to predicting recidivism outcomes. As a result, Brown et al (2009) suggested that future research is required to explore whether or not positive affect is capable of dynamic change over time for periods longer than five months, and whether or not any such changes could be related to recidivism outcomes for adults on probation (Brown et al., 2009).

Given the valuable insights gained from Brown et al.'s (2009) pioneering research, the current study represents a part of a larger scale attempt to replicate the Brown et al.'s (2009) results in a larger correctional sample of both adult males and females, who were also followed-up over a longer time period (up to 18 months) on community probation. Originally, the current research was designed to achieve as close of a replication of Brown et al.'s (2009) study design as possible; however, due to in-vivo constraints that eventuated during data collection, as well as the inherent geographical sample differences (Canadian vs. USA participants), the current study's final sample had some similarities, as well as some differences, with Brown et al.'s (2009) sample. Both similarities and differences between the two studies will be outlined and further discussed in the context of the results comparison as part of Chapter 5 (Discussion).

Most importantly, the focus of the current thesis is specifically on positive and negative affective dynamic predictors of recidivism, which are here explored in further depth and across different affect dimensions. The current study is therefore an attempt to both replicate and extend Brown et al.'s (2009) findings, particularly in relation to the dynamic affect-based prediction of criminal recidivism.

Rationale for the Current Research

Notwithstanding the significant body of research pointing towards the importance of emotions as motivators of human behaviour, in the field of criminology little is known about the relationship between negative emotions and re-offending behaviour, and even less so about the potential relationship between positive emotions and re-offending behaviour. The current study therefore seeks to address this gap in knowledge by exploring in more detail the ability of dynamic affect to predict recidivism across both its valence dimensions (positive and negative affect), and its behavioural activation dimension (low activation and high activation affect). Additionally, the natural (i.e., not experimentally induced) degree of change in dynamic affect over time across both dimensions was examined, in addition to exploring whether differing degrees of change exist in relation to well-established static recidivism risk factors, such as participant's age, gender and recidivism risk category. Given the scarce body of research available on dynamic affect and recidivism (especially in relation to positive affect), no specific hypotheses on the potential links were made, with this study being conceptualised as primarily exploratory in nature. The current research is also a part of a larger-scale attempt to both replicate and extend the pioneering study findings by Brown et al. (2009). The current study results will be discussed in the light of broader theories and research on emotions and behaviour, as well as more specifically in relation to its commonalities and differences with Brown et al.'s (2009) study findings.

Chapter Three: Method

Participants

Selection Criteria

Participants for this study were recruited at two partner community corrections agencies in the United States, both of which supervise individuals who were serving sentences on probation. One community agency was a state probation agency in Texas situated within a Hispanic-majority county. The second agency was a federal probation agency in Oklahoma state, which neighbours the state of Texas.

In the current study, efforts were made to recruit probationers shortly after the beginning of their supervision orders, to maximize retention in the longitudinal design; however, no participant exclusion criteria were specified for study participation. Attempts were made to contact all individuals who were currently supervised at the agencies. As both agencies only supervised adults aged 18 and above, all youth below 18 year old were assumed to be automatically excluded. However, it was later discovered that a 17 year old individual had been convicted as an adult and had accidentally participated in the study. Due to study ethical considerations, the minor participant's data was removed from the data analysis.

Sample Demographics

The overall study sample consisted of a total of 352 participants who were recruited while on probation (i.e., serving their sentence in the community). Two hundred and eighty participants were recruited from the Texas state probation agency (comprising 79.5% of the total total sample), and 72 participants were recruited from the Federal probation agency (comprising 20.5% of the total sample). As outlined in Table 1, both subsamples were similar in their gender distributions, both being approximately 75% male and 25% female. The average age of study participants fell in the mid-30s ($M = 35.21$, $SD = 12.18$) for the state sub-sample to early-40s ($M = 42.39$, $SD = 11.41$) for the federal sub-sample. Notably, this is also the stage of the life when individuals are more likely to be in a process of desistance from crime. Other participant demographic information (including race/ethnicity, marital status, and education status) were either not reliably coded or were inconsistently provided by the two probation agencies, and as such were not collected directly during data collection.

Table 1 outlines several characteristics of the sample of participants (displayed separately by agency location). Participants' criminal history, recidivism risk category, demographic (gender, age) and revocation information were collected via official files provided by the probation department partner agencies. Both state and federal agencies provided the file information on an ongoing basis through 2018-2019, as part of ongoing recruitment for this study. Both agencies also updated the study participant files with new revocations and arrests across time.

The data collection for this study was completed on 30th of June 2019. However, file information on recidivism rates for a group of participants in the state sample was last obtained on May 29, 2019. As a result, a group of participants in the state sample did not have follow-up recidivism file information because they participated in the study after their file information was last obtained on May 29, 2019. For the federal probation agency, however, the participant file information was last provided in September 2019, after the study data collection had ended on June 30, 2019, so the federal subsample recidivism rates are more updated than the state recidivism rates.

Table 1

Descriptive Statistics (Sample Sizes, Percentages, Means, and Standard Deviations) of Study State and Federal Subsamples

Variable	**State Probation Subsample (*n* = 280)**	**Federal Probation Subsample (*n* = 72)**
	n (%)	*n* (%)
Gender		
Male	205 (73.2%)	55 (75.3%)
Female	71 (25.4%)	16 (22.2%)
Missing Data	4 (1.4%)	1 (1.4%)
Language		
English	226 (80.7%)	71 (98.6%)
Spanish	54 (19.3%)	1 (1.4%)
Age at Start of Supervision	*M* (*SD*) = 35.21 (12.18) *n* = 276, Missing Data *n* = 4	*M* (*SD*) = 42.39 (11.41) *n* = 71, Missing Data *n* = 1
Most Serious Index Offence		
Driving Under the Influence of a Substance	97 (34.6%)	-
Substance Use / Possession / Dealing	53 (18.9%)	23 (39.1%)
Non-violent Crime	60 (21.4%)	23 (31.9%)
Violent Crime	48 (17.1%)	16 (22.2%)
Sexual Crime	16 (5.7%)	9 (12.5%)
Technical Violation	1 (0.4%)	-
Missing Data	5 (1.8%)	1 (1.4%)
Risk Level		
Low	52 (18.6%)	21 (29.2%)
Moderate	153 (54.6%)	40 (55.6%)
High	24 (8.6%)	10 (13.9%)
Missing Data	51 (18.2%)	1 (1.4%)
Recidivism Events	*n* = 38 (8.6%)	*n* = 16 (22.2%)
New Arrest	27 (71.0%)	6 (37.4%)
Revocation (Other)	5 (13.2%)	9 (56.3%)
Violation of Conditions	6 (15.8%)	1 (6.3%)
*Days From Supervision Start to Recidivism**	*M* (*SD*) = 372.75 (168.74) *n* = 24, Missing Data *n* = 256	*M* (*SD*) = 437.20 (255.23) *n* = 27, Missing Data *n* = 1

*This variable is relevant only for the 54 individuals with recidivism events.

Table 1 further outlines the participant recidivism risk level information as categories (low, moderate, high) to assist with comparison across state and federal risk instruments.

Although the risk assessment tools used by both agencies shared highly similar domains, the state agency utilized a slightly different risk assessment tool for individuals who were convicted of a felony as opposed to a misdemeanour under the United States law, which were both different from the risk assessment tool used by the federal agency. These tools are subsequently described in greater detail in Measures. As a result, three slightly different assessment tools were used to assess participant's recidivism risk, dependent on the place of recruitment and / or participant offence history. This did not allow for a direct risk score comparison between the federal and the state agency scores. Consequently, participants' recidivism risk was presented as categories (i.e., low, moderate or high risk of recidivism).

To further assist the reader with understanding the differences in the United States offence terminology, a felony is defined as a serious crime which is analogous to an indictable crime within the Australian law (i.e., crime that requires a trial within a Superior court). This type of serious crime can range from white-collar crimes to manslaughter and murder. In contrast, a misdemeanour is defined as a less serious criminal offence that can attract up to a maximum of 12 months imprisonment under the United States law. Misdemeanour offences mainly include driving under influence of substances, possession of an illegal substance and thefts ("Civil infractions vs. misdemeanors vs. felonies," 2018).

For both state and federal study subsamples, the majority of the participants belonged to the moderate risk level category (54.8% in state subsample, 55.6% in federal sub-sample), with participants in the low risk category being second largest cohort comprising of 18.6% for the state sample, and 30.1% participants for the federal sample. Notably, the high risk of recidivism category was the least populated in both subsamples, comprising of 8.6% (or 24 participants) of the state sample, and 13.7 % (or 10 participants) of the federal sample. The missing data for the risk categories was higher for the state sample (18.2%) than for the federal sample (1.4%).

In total, 54 recidivism events were recorded for the overall study sample of 352 participants. The recidivism events were spread across 51 recidivist participants, and this difference was a result of three study participants having recidivated twice during the course of the study. The number of people with no follow-up data (because they participated after we pulled the follow-up data) is twenty-six. Notably, the majority of participants did not recidivate during the study length.

With regards to index offence history among the state probation sub-sample, the most common index offence for this participant group was driving under influence of a substance (34.6%), followed by non-violent crime (21.7%), substance use/possession/dealing (18.9%), violent crime (17.1%), sexual crime (5.7%) and technical violation (0.4%). The most common index offence for the federal probation sub-sample was substance use/possession/dealing (39.1%), followed by non-violent crime (31.9%), violent crime (22.2%) and sexual crime (12.5%).

Measures

For this study, seven different questionnaires were selected and administered to the participants on up to four occasions over time: Personal Outcome Expectancies for Crime (POE-C) Questionnaire (Lloyd & Serin, 2012), Personal Outcome Expectancies for Desistance (POE-D) Questionnaire (Lloyd & Serin, 2012), Agency for Desistance Questionnaire (ADQ) (Lloyd & Serin, 2012), Measures of Criminal Attitudes and Associates (MCAA) (Mills, Kroner, & Forth, 2002), Criminal Self-Efficacy Scale (Brown et al., 2009), Positive Affect Negative Affect Schedule (PANAS) (Watson et al., 1988), and UPPS+P Impulsive Behaviour Scale (Whiteside & Lynam, 2001). In total, there were 285 unique questionnaire items within these seven questionnaires that were presented to participants, with the same number of items repeated in full in each of the three administration sessions. However, the current research has focused only on a select number of administered measures for the data analysis, with variables of interest centred on participants' positive and negative emotional states, their re-offending risk levels and their recidivism outcomes.

Recidivism

Re-offending outcomes data were provided by the Texas State Probation Agency and Federal Probation Agency of the United States Department of Corrections. Recidivism outcomes were followed for up to 2 years and 4 months, from the start of data collection on 22 May 2017 until end of May 2019 for the state sample, and until September 2019 for the federal sample.

Recidivism outcomes in this study included all variations of recidivism outcomes, including breaches. In relation to the overall number of recidivism events for the total participant sample of 352 individuals, 54 recidivism events (15.3%) occurred before the completion of the study data collection. Specifically, for the state probation sub-sample of 280 individuals, the total number of recidivism events was 38 (8.6 %), while there were 16 recidivism events (22.2%) in the federal subsample of 72 individuals. Notably, 54 recidivism events were spread across 51 participants, a result of three study participants' recidivating twice during the course of the study. The study protocol had allowed for participants who had re-offended during the course of the study to restart their study assessments again from Time 1, which resulted in three additional recidivism events for three participants who recidivated once, restarted the study, then recidivated for a second time before the study was completed. The reason re-entry into study was allowed was because our unit of analysis was not the individual person, but the reintegration period of attempted desistance, which could have occurred a few times for the same person over time. The reasons for recidivism were varied; the most common recidivism event in the state subsample was a new arrest (71.0%), followed by a violation of probation conditions (15.8%), and other revocation (13.2%). The most common recidivism event in the federal subsample was other revocation (56.3%), followed by a new arrest (37.4%), and violation of conditions (6.3%). The recidivism data was provided to us by the partnering agencies, as they were recorded. While recidivism due to 'revocation' could have been due to an arrest or to an incident that did not result in a charge, unfortunately this level of detail was not available from the data provided by the partnering agencies.

Positive and Negative Emotions

Emotions were assessed using a modified version of the Positive Affect Negative Affect Schedule (Watson et al., 1988). The scale was modified by Brown, St Amand and Zamble (2009) to take previous criticisms (Nemanick & Munz, 1994) as well as past corrections specific research into account (Zamble & Quinsey, 1997). Although the PANAS is one of the most frequently used and psychometrically sound measure of perceived emotional states, it had also been criticised for not fully assessing all aspects of the theoretical framework it sought to measure, i.e., the Circumplex Model of Emotions (Plutchik & Conte, 1997; Russell, 1997). The Circumplex model suggests that emotions are best conceptualised along two bipolar dimensions: 1) high arousal / activation (e.g., active, excited) vs low arousal / activation (e.g., inactive, bored); and 2) pleasure (e.g., content, happy) vs. displeasure (e.g., sad, angry). Nemanick and Munz (1994) argued that PANAS does not adequately capture the low end of the bipolar dimensions (e.g. low activation and low displeasure). To correct for this, the original PANAS scale was revised by Brown et al. (2009), who added new adjectives representing the lower end of the bipolar dimensions of the Circumplex Model of Emotions (Brown et al., 2009). The additional adjectives were selected from examples provided by Russell (1997) and Kercher (1992) due to their apparent face validity, but also due to their consistency with grade 8 reading level, which made them appropriate for corrections population (Kercher, 1992; Russell, 1997). Additional negative emotions were also added because these emotional constructs were previously found to be related to recidivism (Zamble & Quinsey, 1997), making the revised PANAS scale even more specific to offender populations (Brown et al., 2009).

As a result, the revised PANAS scale is comprised of 30 items and two subscales: Positive Affect Schedule and Negative Affect Schedule. The Positive Affect Schedule contained 12 affective states (e.g., excited, proud, at ease, peaceful), while Negative Affect Schedule contained 18 states (e.g., bored, anger, depressed, nervous). Relatively neutral PANAS items such as 'calm', sleepy', and 'quiet' were assigned to the negative affect schedule due to their higher correlations with items from the negative PANAS subscale. PANAS scale items assess for the amount / frequency of affect experienced by the individuals over the last 14 days (i.e., "Please indicate how much you have been feeling this way during the last two weeks."), using a 5-point Likert scale ranging from: 1- 'not at all' to 5- 'very much'. Total PANAS sub-scales scores could range between 12 and 60 for the *Positive Affect Schedule*, with higher scores reflecting higher levels of reported positive emotions, while scores for the *Negative Affect Schedule* could range between 18 and 90, with higher scores reflecting higher levels of reported negative emotions.

Additionally, the PANAS scale was subdivided to measure and calculate the *Positive Affect-High Activation* subscale, which included seven PANAS positive emotions that are high in behavioural activation (interested, alert, excited, active, enthusiastic, proud, strong). In contrast, the *Positive Affect-Low Activation* subscale included positive emotions low in behavioural activation and was comprised of the remaining 5 items of the *Positive Affect Schedule* (calm, at ease, content, peaceful, relaxed). Similarly, the *Negative Affect-High Activation* PANAS subscale included only negative emotions high in behavioural activation and consisted of 7 items (uptight, angry, ashamed, stressed, nervous, guilty, irritable), while the *Negative Affect-Low Activation* subscale included negative emotions low in behavioural activation and was comprised of the remaining 11 items of the *Negative Affect Schedule* (hopeless, numb, quiet, depressed, inactive, sleepy, miserable, bored, sad, unhappy, tired).

The revised PANAS has previously demonstrated strong reliability (Cronbach's alpha = .84–.90; (Brown et al., 2009)), which was in line with the original PANAS that has demonstrated strong reliability (Cronbach's alpha = .86–.90; (Watson et al., 1988)) and strong convergent (validity coefficient: $r = .67$) and discriminant validity (validity coefficient: $r = -.31$) with measures of depression and anxiety (the HADS and the DASS) (Crawford & Henry, 2004).

Recidivism Risk Instruments

Risk of reoffending was measured as part of standard practice by the two probation agencies via two different instruments: (i) Federal Post Conviction Risk Assessment (PCRA), which was administered by the Federal Probation Agency of the United States Department of Corrections for the federal participant sample, and (ii) The Texas Risk Assessment System (TRAS), which was administered by the Texas State Probation Agency of the United States Department of Corrections for the state participant sample. Both assessment tools are internally developed standardised risk assessment tools used by the Texas Community Supervision and Corrections Department (CSCD) and the Oklahoma Federal Probation of the U.S. Courts, which ultimately categorise each individual into a low, medium or high risk of recidivism group based on common evidence-based risk factors. For TRAS, these risk categories included criminal history, education and employment, family, neighbourhood, peers, substance abuse, and criminal attitudes (Lovins & May, 2015). For PCRA, the risk categories included criminal history, education/employment, substance abuse, social networks, cognitions, other (housing, finances, recreation) and responsivity factors (Courts, 2011).

Both PCRA and TRAS were previously validated for predicting recidivism (Courts, 2011; Lovins & May, 2015). Although all risk assessment tools share similar risk category domains, the state agency utilized a slightly different risk assessment tool for individuals convicted of a felony versus a misdemeanour (TRAS and a TRAS variant), and the federal agency utilized another tool (PCRA), which could not be directly compared with the state agency's TRAS scores. As a result, in all of our analyses, the recidivism risk level was retained as risk categories (low, moderate, high) and not individual scores.

Procedure

Data Collection

The study procedure was reviewed and approved by the Human Subjects Protection Office within the National Institute of Justice, and the institutional review boards at three universities: University of Texas at El Paso, Carleton University, and Swinburne University of Technology. The partner probation agencies had also reviewed the proposed study procedure prior to participant recruitment. The study procedure also involved a focus group conducted at each probation site. This component of the study involved separate recruitment procedures and non-overlapping inclusion criteria.

For recruitment purposes, research assistants were provided access by each agency to a dedicated office room and contact information for the probationers. The research assistants phoned potential participants and informed them of the opportunity to attend a voluntary session at the probation office to answer a series of questionnaires asking about their thoughts and emotions about themselves and crime. Upon attending a scheduled session, participants read information about the study and acknowledged informed consent on a computer tablet, before privately completing questionnaires on the tablet. Participants were informed that they would be contacted up to two additional times and invited to complete the questionnaires again in subsequent sessions. They were debriefed about the purpose of the study at each session they attended. Participants received a $20 gift card at the end of their first session, a

$25 gift card at the end of their second session, and a $30 gift card at the end of their third session.

The hand-held computer tablets presented participants with 285 unique questionnaire items, with these same items repeated in full in each of the three sessions. Offender participants were asked to self-report their personal perceptions of the costs and benefits of crime, costs and benefits of attempting to stay crime-free, attitudes, impulsive traits, and positive and negative emotions over the last two weeks. Data collection sessions began on 22nd of May, 2017 and concluded on 30th of June, 2019. On average, each data collection session lasted for 52 minutes, although some were shorter (when participants did not complete all items) or longer (up to approximately 90 minutes).

The data collection took take place in a private room in the probation office, and the questionnaire responses were recorded on computer tablets owned by the researchers. The computer tablets were encrypted and password-protected, with only the research assistants and Principal Investigator (PI) having had the knowledge of the password. Tablets remained in the possession of the research assistants, who were not employed by the probation offices. To protect participants' privacy, none of the questionnaire responses were provided to criminal justice staff. In addition, participants were able to answer all questions privately on the tablets without the research assistant being able to view their responses.

The questionnaire completion took place through a software program called Qualtrics. The computer tablets remained off-line during data collection (i.e., no internet connection). After questionnaires are completed, participant answers were stored within the Qualtrics software on the encrypted, password-protected tablets. The research assistants were responsible for uploading the responses to the PI's Qualtrics account, once they had connected the tablets to the internet at an off-site location. Data transfer from the tablets to the PI's main account occurred entirely within Qualtrics' system of software, further ensuring data privacy. When connected to the internet, the Qualtrics system was able to upload participants' responses through the tablet software into the Principal Investigator's main account, where all collected participant data was stored. The Principal Investigator could then access the data through a password-protected online account. As participant data was uploaded into the main account, the participant responses were deleted from the computer tablets. The research assistant was therefore also unable to access participant responses, even when in possession of the computer tablet.

Participants were given a gift card each time they participated to off-set the cost of participation and to help ensure data are collected at multiple time points for each individual. They also received a debriefing form following each occasion of participation. Across the same time period of data collection, supervision staff at the probation offices provided the researchers with additional demographic, risk and offence history data about participants; these data were collected as part of routine, standard practice at these sites. In particular, ratings of recidivism risk factors, which were completed by supervision officers, were also provided to the research team. Secondly, supervision staff provided information about any new criminal behaviour outcomes to the researchers (i.e., date and nature of technical violations, date and nature of arrest). Third, file information including criminal history and participant demographic information were also provided to the investigators.

In total, 654 data collection sessions were completed with 353 individuals. Unfortunately, four participation sessions were lost when a tablet malfunctioned, leaving a total of 650 sessions for analysis from 352 individuals. Also, although the study was designed to involve a maximum of three participation sessions per individual, two individuals were mistakenly invited to participate in a fourth session each.

Minimizing Attrition

Recognizing the substantial time commitment of participation in this study, several strategies were implemented to maximize the follow-up recruitment and to minimize the amount of missing data. For example, care was also taken to minimize potential systematic patterns of missing data across the questionnaire items. In particular, the questions were presented on computer tablets as this format was found to be engaging for participants in criminal justice settings compared to paper-and-pencil methods (King et al., 2017). Second, following the strategy described by Pickett and colleagues (2014), participants were allowed to self-navigate through the questions by making a choice at three points in the questionnaire process regarding which type of questions they would like to be presented with next. The questions were also grouped into broad categories (e.g., "thoughts about myself", "how I'm feeling") for participants to select from, as giving participants choice in the topic of question they would like to answer next was seen as more engaging overall. Further, within each category, the questionnaire items were presented in a random order, in order to combat systematic patterns of missing data due to question fatigue. Third, all materials were translated from English so Spanish, thus allowing Spanish-fluent participants a choice to complete the study either in Spanish or in English (including informed consent and debriefing forms). Fourth, as described above and encouraged by Hanson and colleagues (2012), participants' time was compensated with a gift card for each session, with increasing amounts for each subsequent session, as a way to encourage study retention.

Data Analysis

Analytical Approaches: Describing Change and Predicting Recidivism

Statistical analyses were used to explore whether positive and negative emotional experiences over time are related to re-offending outcomes. In this study, positive and negative affect – total, high activation and low activation (as assessed by the two total and four subdivided PANAS subscales), participant gender, age at the start of probation and risk of recidivism category (as assessed through the partner agencies data) were the independent variables used to predict recidivism outcomes (also provided by partner agencies data) which was the dependent variable. The alpha level was set at .05 to classify findings as statistically significant. Analyses included 650 assessment occasions across three assessment waves.

Hypothesis testing analyses were conducted using two statistical packages: 1) IBM SPSS Statistics (version 27) and 2) R, an integrated suite of free software facilities used for complex statistical data manipulation, calculation and graphical display. In particular, R provides a variety of statistical techniques, including linear and nonlinear modelling, classification, time-series analysis, clustering and others, as well as well-developed graphical techniques, for data analysis ("R: A language and environment for statistical computing," 2013). R was used to complete all multilevel modelling and Cox regression survival data analyses in this study. Specifically, we have used the R- 'CoxPh' package for Cox regression analyses, and the R- 'lmer' package for multilevel modelling. Further details regarding the specifications within these analyses are freely available via an online search.

Multilevel Modelling

Multilevel modelling, a variant of multiple regression is commonly used in research to analyse hierarchical data with a nested structure. This study dataset had a two-level nested structure; occasion-level variables (Times 1, 2, 3 and 4) were nested within the individual-level variable (each participant). Multilevel modelling was utilised to explore change in self-reported emotion (PANAS scale) over time by examining how ratings-based scores changed and if degree of change at the occasion-level differed systematically with variables at the individual-level. Importantly, the advantages of using multilevel modelling over repeated measures ANOVA or ANCOVA are in the flexibility of assumptions in unbalanced data structures with missing data, removing the need to complete data imputations for the missing values in this dataset. (Imputation is the process of replacing missing data with substituted values, as calculated by certain rules.) In particular, multilevel modelling does not require assumptions of homogeneity of regression or the independence of observations to be met, and allows for presence of missing data which is assumed to be missing at random (Snijders & Bosker, 1999). We examined multilevel models in which the intercept and all occasion-level slopes were both fixed and random, to allow for maximal data exploration.

Cox Regression Survival Analysis

Cox regression survival analysis is a semi-parametric survival method that can incorporate multilevel data across time, exploring the relationship between predictor variables and the likelihood of an event (e.g. recidivism) occurring, while taking time to the event into account (Cox, 1972; Singer & Willett, 2003). It is a highly utilised statistical model in corrections research as it readily incorporates inherent features of reintegration datasets. For example, it is common in longitudinal correctional studies that (a) not all individuals will experience the predicted event (i.e., re-offending), (b) follow-up time will vary between individuals, and (c) the predicted event may occur after varying lengths of time. While traditional procedures such as multiple logistic regression examine the relationship between a variable(s) and a binary outcomes measure (e.g., did not re-offend vs. re-offended) over a fixed period of time, survival analysis examines the relationship between a variable(s) and a binary outcome measure while allowing survival time to vary on a continuous time scale. In short, survival analysis is a statistical technique that accounts for the length of time that occurred (i.e., survival time) prior to a particular event (e.g., re-offending). For recidivists, survival time is generally recorded as the length of time between the release date and their recidivism date, which can be coded in days, months or years. For non-recidivists, survival time is generally coded as the length of time between their release date and the study termination date (i.e. when research follow-up had ceased). Survival analysis is common in correctional outcome studies because it naturally controls for variable follow-up across participants (Singer & Willett, 2003).

Cox regression analysis generates regression parameters using partial likelihood estimation procedures (Cox, 1972; Kalbfleisch & Kalbfleisch, 2002; Liu, 2012). This type of analysis is helpful as it accounts for the fact that an event can occur at different times for different people simultaneous to the fact that the independent variable scores may be updated across time sporadically for some people but not others. Like multilevel modelling, Cox regression also allows uneven assessment schedules, so missing data do not need to be imputed.

Further, it allows for regression parameters to be estimated without making assumptions about the shape of the baseline survival function. It also allows the researchers to compare the relative contribution of multiple variables simultaneously, regardless of whether or not they are continuous or dichotomous, similarly to multiple regression. Ultimately, Cox regression is the only model in the class of survival analyses that is able to deal with time-dependent co-variates (Singer & Willett, 2003).

Statistical power in survival analyses is dependent on several factors, such as the total number of study participants, the length of the study follow-up period and the base rate of the event (outcome) researchers are trying to predict. Longer follow-up periods lead to a greater statistical power, as longer follow-up periods are also associated with a higher possibility of a greater number of events of concern (failures). Previous research had recommended that the follow-up period should be sufficiently long to allow at least half of participants to fail (Singer & Willett, 2003). Methods for determining statistical power for survival analysis are readily available for research designs involving two or more group comparisons (e.g., treatment vs. control group), but group comparisons are not the design of the current study. As a result, the statistical power analysis could not be completed given the formula requires two different median survival times (e.g., one that corresponds to a control group and another corresponding to a treatment group).

It is also important to note that in typical regression, it is not recommended to run models where there are less than ten participants per predictor, which for our Cox regression models means the presence of less than 10 recidivists per predictor, not just ten participants in total. In this study, all models are exploratory, but with 40 recidivists in the study sample, any models presented with more than four predictors are so low powered as to be not recommended. However, because all models were built iteratively in an exploratory fashion (i.e., testing each unique predictor before testing multiple predictors in combined models), we sometimes broke from this recommendation in order to demonstrate the preferred model (even though it was statistically under-powered) or to examine exploratory hypotheses (Hanson et al., 2020; Moons, Royston, Vergouwe, Grobbee, & Altman, 2009).

In the current study, the Cox Regression survival analysis used the most recent PANAS score (the one in closest proximity to the event of interest) to predict the event of interest.

Chapter Four: Results

Attrition from the Probation Sample

In total, 352 individuals were recruited for the study (280 participants from the state agency, and 72 participants from the federal agency), attending at least one data collection session. The rate of recruitment for a second session was 52.8% (i.e., 186 / 352 participants), with 30.9% (i.e., 109 / 352 participants) returning for a third assessment session. Table 2 provides a brief comparative overview of participants who returned vs. participants who dropped out from the study at both Times 2 and 3. Notably, no significant differences were found between the two groups at both time points with regards to their gender, language, and their index offence. However, there was a statistically significant difference between Time 1 and Time 2 study completers (χ^2 (2, N = 300) = 8.59, $p < .05$), such that significantly more low recidivism risk category participants returned to compete the study at Time 2, while significantly less high recidivism risk category participants returned at Time 2. It is likely that low recidivism risk participants are more socially engaged and thus more willing to continue volunteer their time to participate in the study, compared to the high recidivism risk participants, who may be less likely to volunteer their time but also more likely to be unavailable for follow-up due to higher re-offending rates. Despite best efforts to maintain assessment waves at consistent time intervals as it was originally planned, in reality the timing of the follow-up assessments was considerably varied / sporadic across different participants. For example, means, standard deviations, minimums and maximums for days from start to Time 1 were 137.96 (116.7); [40 - 757], for Time 2 were 266.13 (153.96); [71 - 770]; and Time 3 were 391.61 (158.24); [88 - 779]. It is for this reason that we have decided not to follow up with average assessment times, as averages would not be indicative of real times, considering extensive differences between minimums and maximums at each time point.

Table 2

Study Continuation vs. Study Dropout: Age, Gender, Most Serious Index Offence and Recidivism Risk Category

Variable	Study Sample (n=352)					
	Time 2			**Time 3**		
	Completers	Dropouts		Completers	Dropouts	
	% (n/n)	% (n/n)	χ^2	% (n/n)	% (n/n)	χ^2
Gender [1]						
Male	77.9% (145/186)	71.4% (115/161)	1.95	78.0% (85/109)	76.9% (60/78)	0.029
Female	22.1% (41/186)	28.6% (46/161)		22.0% (24/109)	23.1% (18/78)	
Language						
English	81.2% (151/186)	87.9% (146/166)	3.05	79.8% (87/109)	83.3% (65/78)	0.37
Spanish	18.8% (35/186)	12.1% (20/166)		20.2% (22/109)	16.7% (13/78)	
Most Serious Index Offence [1]						
Driving Under the Influence of a Substance	34.1% (63/185)	20.9% (34/162)		34.0% (36/106)	34.6% (27/78)	
Substance Use / Possession / Dealing	21.1% (39/185)	22.8% (37/162)		20.7% (22/106)	20.5% (16/78)	
Non-violent Crime	20.0% (37/185)	29.1% (47/162)		20.7% (22/106)	20.5% (16/78)	
Violent Crime	16.7% (31/185)	20.4% (33/162)	11.82	11.3% (12/106)	23.1% (18/78)	12.05
Sexual Crime	7.6% (14/185)	6.8% (11/162)		12.3% (13/106)	1.3% (1/78)	
Technical Violation	0.5% (1/185)	-		1.0% (1/106)	-	
Recidivism Risk Category [1]						
Low	30.2% (48/159)	17.7% (25/141)		39.5% (32/95)	28.2% (22/69)	
Moderate	61.6% (98/159)	66.7% (94/141)	8.59*	41.3% (56/95)	50.0% (39/69)	0.86
High	8.2% (13/159)	15.6% (22/141)		6.4% (7/95)	10.3% (8/69)	
	M (*SD*)	*M* (*SD*)	*t*	*M* (*SD*)	*M* (*SD*)	*t*
Age at Start of Supervision	36.76 (11.83)	36.56 (12.95)	-0.16	37.35 (11.97)	35.94 (11.91)	- 0.804

*$p < .05$; **$p < .001$, *** $p < .0001$

[1]Note: 47 participants were missing recidivism risk category information; 3 participants were missing gender information and 6 participants were missing the index offence information. These participants were not included in the Chi Square analyses.

Data Screening

Preliminary Data Screening

All variables were first examined for data entry accuracy and the presence of missing values using IBM Statistical Package for the Social Science (SPSS), Version 27. Following this, preliminary analyses involving the six PANAS Positive and Negative Affect subscales were conducted before proceeding with traditional data screening techniques.

Reliability

Internal consistency (a measure of scale reliability) for the six dynamic PANAS subscales (Negative Affect Total, Negative Affect High Activation, Negative Affect Low Activation, Positive Affect Total, Positive Affect High Activation, Positive Affect Low Activation) were assessed by calculating each subscale's Cronbach's alpha for the participant sample across three different time points. Cronbach's alpha is the most commonly calculated reliability co-efficient for any single testing occasion, where a multiple-item scale is administered to measure a construct (Cronbach, 1951). Cronbach's alpha results for PANAS subscales are presented in Table 3 below. All PANAS positive and negative affect subscales demonstrated strong internal consistency across all three time points.

Table 3

PANAS Positive and Negative Affect Subscales Reliability Estimates

PANAS Subscale	Time 1	Time 2	Time 3
	Cronbach's Alpha (*n*)	Cronbach's Alpha (*n*)	Cronbach's Alpha (*n*)
PANAS Negative Affect Total	.92 (279)	.93 (146)	.90 (71)
PANAS Negative Affect High Activation	.85 (317)	.84 (161)	.79 (88)
PANAS Negative Affect Low Activation	.89 (299)	.91 (160)	.83 (84)
PANAS Positive Affect Total	.89 (292)	.91 (153)	.89 (85)
PANAS Positive Affect High Activation	.82 (310)	.83 (162)	.83 (91)
PANAS Positive Affect Low Activation	.85 (317)	.87 (167)	.86 (95)

Missing Data

A degree of missing data was present in this study dataset for all independent variables. Among the categorical independent variables, the percentage of missing data for participant age across the whole sample was 0.8%, for gender was 0.8% and for the recidivism risk category was 13.7%. Completeness of these records was dependent upon the data quality retained and provided by the probation office partner agencies.

For the continuous independent variables in this study (i.e., the six PANAS Negative Affect and PANAS Positive Affect subscales), the percentage of missing items across the whole sample was 23.4% for PANAS Negative Affect Total and 18.3% for PANAS Positive Affect Total. In particular, PANAS Negative Affect Total scale had 16.6% participants missing only 1 item, 2.5% participants missing the 2 scale items, and 0.6% missing 3 items on the 18 item scale. On the PANAS Positive Affect Total scale, there were 11.4% participants missing 1 item only, 3.1% of participants missing 2 items, and 0.3% of participants missing 3 items on the 12 item scale. Overall, there was very little missing

PANAS data across different time points, with most missing data being related to participants not returning to participate for the 2nd or 3rd time. We conducted the Little's MCAR test for the entire PANAS scale. The Little's MCAR test results; $\chi 2$ (2587, N = 627) = 2628.51, p = .280; were non-significant, indicating that the PANAS missing data was missing completely at random. We chose to allow up to 20% of missing items for the dynamic affect scales in this study sample, for several reasons: (i) if a participant completed 15 out of 18 items on the PANAS Negative Affect Total scale, for example, we considered that 80% of completed items was a good enough indication of their overall negative affect; (ii) if we applied a more conservative missing item allowance in this dataset, the number of participants would have been substantially reduced, and (iii) the overall study design was such that, due to a relatively high number of items (282 questions) participants were asked to complete per each assessment session, the potential for missing items due to question fatigue was substantial.

To address the missing data across all six dynamic PANAS subscales, we first prorated the PANAS Negative and Positive Affect Total scales for participants who had up to 3 missing data points (because 3 missing items was below the 20% missing data allowance we set per predictor variable), and for the PANAS Negative / Positive Affect High Activation and Low Activation scales that contained fewer items, we followed the same procedure but prorated scores for the participants who were missing up to 1 item only, to remain in line with the below 20% missing items allowance per variable. The prorated versions of all of the PANAS Positive and Negative Affect subscales were subsequently used for the data analyses.

Notably, the main statistical data analyses selected for this study (i.e., multilevel modelling and Cox regression survival analysis) were most appropriate due to the hierarchical nested structure of this dataset, while simultaneously allowing flexibility of assumptions regarding unbalanced data structures. This feature allowed missing data across different assessment time points without imputation, meaning scores were only prorated for completed data collection sessions whereas data missing due to study dropout were not imputed or prorated in this dataset.

Table 4

PANAS Positive and Negative Affect Missing Data At Times 1, 2 and 3

N items missing	Time 1				Time 2				Time 3			
	N	*M* (*SD*) pro-rated scores	% missing of total *N* = 352	% missing of Time *N*	*N*	*M* (*SD*) pro-rated scores	% missing of total *N* = 352	% missing of Time *N*	*N*	*M* (*SD*) pro-rated scores	% missing of total *N* = 352	% missing of Time *N*
PANAS Negative Affect												
0	279				146				71			
1	50				29				29			
2	12				3				1			
3	1				1				2			
> 3 but < 18	3				4				1			
All 18 items	7				4				5			
Did not participate	0				165				243			
		35.1 (14.02)	2.8%	2.8%		34.4 (14.2)	49.1%	4.3%		33.8 (12.5)	70.7%	5.5%
PANAS Positive Affect												
0	292				153				85			
1	39				20				14			
2	10				7				3			
> 2 but < 12	4				2				2			
All 12 items	7				5				5			
Did not participate	0				165				243			
		40.4 (10.5)	3.1%	3.1%		41.6 (11.04)	48.9%	3.7%		41.2 (10.6)	71.0%	6.4%

Final Data Screening

Once the pre-screening procedures had been completed, all independent variables were further examined for normality (via histogram, Q-Q plots, skewness and kurtosis tests), for linearity and homoscedasticity (via scatter plots), for multivariate outliers (via calculation of Mahalanobis distance), as well as for any violations of the proportional hazards assumption. Aside from the screening test of for proportional hazards assumption, which was completed once using the entire data set, all other data screening procedures were all examined separately at each wave of data collection (i.e., independently for Time 1, Time 2 and Time 3), to ascertain that the assumptions have been upheld across time and at different stages of data collection.

With regards to normality testing for all variables across all three time points, the original scanning of the histogram plots revealed a degree of skewness was visually present across all variables. However, on further analysis, skewness was deemed as not significantly different from a normal distribution, due to there being no visible major departures from the straight line on the Q-Q plots, as well as there being no above-threshold kurtosis nor skewness ratios indicated.

With regards to linearity and homoscedasticity testing, the scatter plots of all variables were also examined across all three different time points. No significant violations of linearity of homoscedasticity were noted for any variable in this dataset.

With regards to multivariate outliers, the Mahalanobis distance test was calculated to determine if any multivariate outliers were present in the dataset (i.e., if any of the study participants had presented with an unusual combination of scores on a combination of two or more variables). As a result of this analysis, two multivariate outliers were identified that were both just outside of the Mahalanobis distance test threshold. A closer inspection of both multivariate outliers had revealed that both were participants who scored unusually high on the PANAS Negative Affect Total subscale, while simultaneously scoring low on the PANAS Positive Affect Total subscale. Aside from this combination of scores being slightly outside of the predominant scoring pattern for all participants across the dataset, both of these participants had notably still scored within the acceptable scale ranges of both PANAS subscales, confirming that neither multivariate outlier was a result of a data entry error. Although slightly unusual, given that the two participants' responses were still in the acceptable scale response range, the two multivariate outliers were not excluded from the final dataset.

The final screening test for the proportional hazards assumption was completed once for the entire dataset, with results indicating that the test for proportional hazards assumption was statistically non-significant for all variables, indicating that this assumption had not been violated in this study data set.

Following the combined results of the final data screening procedures as outlined above, no further variable transformations were deemed necessary prior to commencing with the main data analyses.

Recidivism: Descriptive Information

The recidivism data for this study sample was generously provided to the research team by the two partnering probation agencies, specifically the Texas state probation agency and the Federal probation agency. Both agencies updated the study participant files with new revocations and arrests across time; however, some inconsistencies in data collection across the two agencies resulted in limitations regarding the final recidivism outcomes data. For example, the data collection for this study was completed on 30th of June 2019; however, the file information on recidivism rates for a group of participants in the state sample was last provided a month earlier, on 29th of May 2019. As a result, a group of participants in the state sample did not have follow-up recidivism file information because they participated in the study after their state probation agency file information was last obtained at the end of May, 2019. For the federal probation agency, however, the participant file information was last provided in September 2019, three months after the study data collection had officially ended on 30th of June, 2019, so the federal subsample recidivism rates are more updated than the state recidivism rates and with slightly longer follow-up.

In total, 54 recidivism events were recorded for the overall study sample of 352 participants across the combined state participants (280) and federal participants (72) subsamples. Notably, the 54 recidivism events were spread across 51 recidivist participants, and this difference was a result of three study participants having recidivated twice during the course of the study. The study recruitment procedures allowed participants who had re-offended during the course of the study to restart their study assessments again from Time 1, which resulted in three additional recidivism events for the three participants who recidivated once, restarted the study, and recidivated for the second time before it was completed. The state and federal agency-provided reasons for recidivism across the total sample were: new offence / arrest (64.1%), revocation of probation - other (25.6%), and violations of probation conditions (10.3%). The average number of days between supervision start and the date of recidivism for all of the study recidivists was 397.5 days (*SD* = 205.5 days). Table 5 below presents recidivism data for the final study sample, however, for more details regarding the recidivism information breakdown specific to the two agency subsamples, please refer to Table 1 (p.90) in the Methods Chapter.

Static and Dynamic Measures

Both static and dynamic variables were present in this study. Static variables included: participants' age at the start of probation, their gender, and their recidivism risk category.

Table 5

Static Measures: Means (M), Standard Deviations (SD), the Observed Range and Percentages (%)

Static Measures	***M* (*SD*)**	**Observed Range**
Age	36.97 (12.34)	18.00-71.32 years
	N (%)	
Gender[1]		
Male	260 (74.7%)	
Female	88 (25.3%)	
Recidivism Risk Category[1]		
Low	74 (24.6%)	
Medium	193 (64.1%)	
High	34 (11.3%)	

[1]Note: 47 participants were missing recidivism risk category information; 3 participants were missing gender information

The dynamic variables, which were repeatedly measured over time, included the six PANAS Positive and Negative Affect subscales: PANAS Negative Affect Total, PANAS Negative Affect High Activation, PANAS Negative Affect Low Activation, PANAS Positive Affect Total, PANAS Positive Affect High Activation and PANAS Positive Affect Low Activation. Table 5 above outlines the means, standard deviations, the observed range and percentages for the study static variables for the final sample (352 individuals). Previously, Table 1 (p.90) was used to present isolated subsamples demographics (280 state agency participants vs. 72 federal agency participants) for subsample comparison purposes.

Table 6

Dynamic Measures: Means (M), Standard Deviations (SD), Possible Range and the Observed Range

Dynamic Measures

PANAS Subscale	Possible Range	**Time 1** *M* (*SD*)	**Time 1** Observed Range	**Time 2** *M* (*SD*)	**Time 2** Observed Range	**Time 3** *M* (*SD*)	**Time 3** Observed Range
PANAS Negative Affect Total	18-90	35.06 (14.02)	18-89	34.42 (14.23)	18-90	33.77 (12.54)	18-77
PANAS Negative Affect High Activation	7-35	13.57 (5.83)	7-35	13.34 (5.72)	7-35	12.76 (5.11)	7-25
PANAS Negative Affect Low Activation	11-55	21.47 (8.90)	11-54	21.05 (9.24)	11-55	21.00 (8.10)	11-53
PANAS Positive Affect Total	12-60	40.36 (10.48)	12-60	41.65 (11.04)	12-60	41.24 (10.61)	12-60
PANAS Positive Affect High Activation	7-35	23.85 (6.29)	7-35	24.33 (6.40)	7-35	24.31 (6.07)	7-35
PANAS Positive Affect Low Activation	5-25	16.46 (5.06)	5-25	17.18 (5.38)	5-25	17.12 (5.18)	5-25

Two main statistical analyses were used to explore the relationship between positive and negative emotions (as measured by the six PANAS subscales), age, gender, risk of recidivism categories and the recidivism outcomes. Multilevel modelling was utilised to explore linear change in emotion (PANAS scale) over time by examining (a) the degree of change across time, and (b) whether the degree of change differed by static factors. Secondly, Cox regression survival analysis, a semi-parametric survival method for investigating multilevel data across time, was used to explore which independent variables over time were most related to subsequent recidivism outcomes. In the following sections, exploratory results from both multilevel modelling and Cox regression survival analyses will be presented together for each independent PANAS Positive and Negative Affect Subscales.

PANAS Negative Affect - Total

Multilevel modelling

The PANAS Negative Affect Total subscale was examined using multilevel modelling (MLM) analyses, to explore if any potential change-over-time patterns occurred for PANAS Negative Affect Total scale for the study adult probation sample. This type of exploratory analysis was considered important to determine if and how total negative affect might fluctuate for adults on supervision over time. Additionally, multilevel modelling was further utilised to explore whether offenders' age at start of supervision, their gender, or recidivism risk category status was related to the degree of total negative affect change over time for this participant cohort. In these models, because the timing of participation was highly variable across the sample, data collection sessions were ordered in time using the number of days (converted to months) since the start of probation. For example, if a participant completed their Time 1 session 75 days into their community probation sentence, the timing of this session was recorded as occurring at 2.48 months (75 / 30.25).

Table 6 below outlines the exploratory MLM results for PANAS Negative Affect Total scale. In Model 1, the intercept value displayed in Column 2 (b = 34.08, SE = 0.89) represents the average PANAS Negative Affect Total score for the study participants across the entire sample (i.e., when individual scores across the different participants and different time points were all taken into consideration). To place this average sample score into context, PANAS Negative Affect Total scores can range from 18 to 90 (see Table 5, p.114; the scale has a total of 18 items rated on a Likert scale from 1-5). Furthermore, Model 1 also shows the Intraclass Correlation Coefficient (ICC) value, a descriptive statistic which indicates how much of the intercept score variance is due to the person, and how much of the intercept variance is due to external circumstances (such as different assessment times). In Model 1, the ICC score of 0.57 indicated that 57% of the total variance in PANAS Negative Affect total scores can be attributed to similarities in scores for the same participant across time, while 43% of total variance can be attributed to differences in assessment scores over time within the same person.

Model 2 (Table 6, random intercept, fixed slope) was subsequently used to examine whether the sample average on the PANAS Negative Affect Total scores would change significantly over time; this model was not significant, showing the sample, on average, did not demonstrate change in scores through time.

Furthermore, in Model 3 (Table 6, random intercept, random slope), where scores were allowed to change at different rates and in different directions (e.g., positive versus negative) for each participant, the average PANAS Negative Affect Total score change over time also remained non-significant. However, the Chi Square analysis of the differences between the Models 2 and 3 was statistically significant with Model 3 providing a statistically significantly better fit to the data compared to Model 2. This better model-to-data fit result indicates that PANAS Negative Affect Total slopes might be significantly changing over time for some of the sample participants; however, the sample's PANAS Negative Affect Total average slope over time remained non-significant.

In Model 4 (Table 6; random intercepts and random slopes), participant age at start of probation was added to MLM to explore whether older versus younger participants reported higher or lower levels of PANAS Negative Affect Total. Table 6 shows that the age estimate for Model 4 was statistically significant (b = - 0.18, SE = 0.073, $\chi^2 \Delta = 5.94$, $p < .05$), indicating that older participants had on average reported significantly lower PANAS Negative Affect Total scores than younger participants. However, although this result was statistically significant, it was also very slight, such that for every year of their increased age, the older participants were likely to report only 1/5 of a point lower on the PANAS Negative Affect Total score. In other words, the age difference between younger and older participants would have to amount to a minimum of five years before an average decrease of one point on the PANAS Negative Affect Total score for older participants would be observed.

Table 7

Multilevel Model Unstandardized Coefficients Predicting PANAS Negative Affect Total Across Multiple Assessments (Minimum of 2, Maximum of 4) and Examining Longitudinal Growth Across Time and Interaction Between Time and Age, and Interaction with Time and Gender Using Restricted Maximum Likelihood Estimation

Variable	Random Intercept	Random Intercept and Fixed Slope	Random Intercept and Random Slope				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Fixed Effects							
Mean Negative Affect Total							
Intercept	34.08 (0.89)	34.08 (0.89)	34.10 (0.899)	34.12 (0.89)	34.13 (0.89)	33.599 (1.017)	33.599 (1.018)
Age at Release	-	-	-	-0.18 (0.073)	-0.18 (0.074)	-	-
Gender (Female)	-	-	-	-	-	2.24 (2.15)	2.25 (2.17)
Linear Slope							
Time in Months	-	-9.79E-5 (0.0897)	-0.048 (0.11)	-0.048 (0.11)	-0.047 (0.11)	-0.051 (0.11)	-0.052 (0.13)
Age at Release	-	-	-	-	-0.0042 (0.0092)	-	-
Gender (Female)	-	-	-	-	-	-	0.0016 (0.27)
Random Effects							
Variance Components							
Level 1 (residual)	83.09	83.37	62.54	62.79	62.58	62.41	62.32
Level 2 (intercept)	109.24	109.22	115.72	111.23	111.44	115.61	115.73
Level 2 (time)	-	-	0.64	0.64	0.65	0.65	0.66
Model Fit							
AIC	3531.1	3533.1	3524.5	3520.6	3522.4	3525.4	3527.4
BIC	3543.4	3549.5	3549.2	3549.3	3555.2	3554.2	3560.3
ICC	ICC = 0.57	-	-	-	-	-	-
χ^2 Δ from prior Model	-	χ^2 Δ = 0.00	χ^2 Δ = 12.61**	χ^2 Δ = 5.94*	χ^2 Δ = 0.20	χ^2 Δ = 1.09	χ^2 Δ = 0.00

Note. N = 450 assessments from 182 individuals

* $p < .05$; ** $p < .001$, *** $p < .0001$ (two-tailed)

In Model 5, we explored if there was an association between participant age and the magnitude or direction of their slope across time, i.e., whether participants of different ages may generally show different degrees of change in PANAS Negative Affect Total across time. However, in Model 5, the age estimate was not statistically significant and did not assist understanding how individuals' PANAS Negative Affect Total scores change across time.

In Models 6 and 7 (Table 6; random intercepts and random slopes), participant gender (female) was added to the model to explore whether changes in PANAS Negative Affect Total over time was related to participant gender. Model 6 showed that, although female participants had on average scored two points higher on the PANAS Negative Affect Total scale, this increase in average scores related to gender was not statistically significant, and therefore not meaningful with regards to any significant gender differences in PANAS Negative Affect Total scores. Furthermore, examining whether average slopes tended to differ in female versus male groups in the sample, Model 7 was also not statistically significant. Overall, Models 6 and 7 (Table 6) demonstrated that participant gender is not a significant consideration in explaining the patterns of PANAS Negative Affect Total change over time for the study sample.

The next variable of exploratory interest in relation to examining the change of PANAS Negative Affect Total scores over time was participants' risk of recidivism category. Notably, these multilevel models were run on a smaller sample due to a larger amount of missing information for the recidivism risk category, as compared to the participant age or gender information. As a result of a smaller sample, Models 1-3 were also re-run in order to explore whether recidivism risk status was related to Negative Affect Total slopes within this smaller sample. Subsequently, in Models 4 and 5, the high recidivism risk category was added to the multilevel modelling. The results of these analyses are presented in Table 7.

Table 8

Multilevel Model Unstandardized Coefficients Predicting PANAS Negative Affect Total Across Multiple Assessments (Minimum of 2, Maximum of 4) and Examining Longitudinal Growth Across Time and Interaction Between Time and Recidivism Risk Category Using Restricted Maximum Likelihood Estimation

Variable	Random Intercept	Random Intercept and Fixed Slope	Random Intercept and Random Slope		
	Model 1	Model 2	Model 3	Model 4	Model 5
Fixed Effects					
Mean Negative Affect Total					
Intercept	33.32 (0.91)	33.36 (0.91)	33.34 (0.91)	33.29 (0.95)	33.22 (0.95)
High Risk Status	-	-	-	0.46 (2.91)	3.82E-5
Linear Slope					
Time in Months	-	-0.12 (0.095)	-0.15 (0.10)	-0.14 (2.96)	-0.013 (2.92)
High Risk Status	-	-	-	-	-0.98 (0.55)
Random Effects					
Variance Components					
Level 1 (residual)	76.03	76.20	71.25	71.33	72.23
Level 2 (intercept)	100.65	99.72	100.81	101.25	99.89
Level 2 (time)	-	-	-	0.17	0.13
Model Fit					
AIC	3066.6	3067.1	3069.3	3071.3	3070.1
BIC	3078.5	3083.0	3093.2	3099.1	3101.9
ICC	ICC = 0.57	-	-	-	-
χ^2 Δ from prior Model	-	χ^2 Δ = 1.51	χ^2 Δ = 1.78	χ^2Δ = 0.026	χ^2 Δ = 3.19‡

Note. N = 395 assessments from 161 individuals

*$p < .05$; **$p < .001$, *** $p < .0001$ (two-tailed)

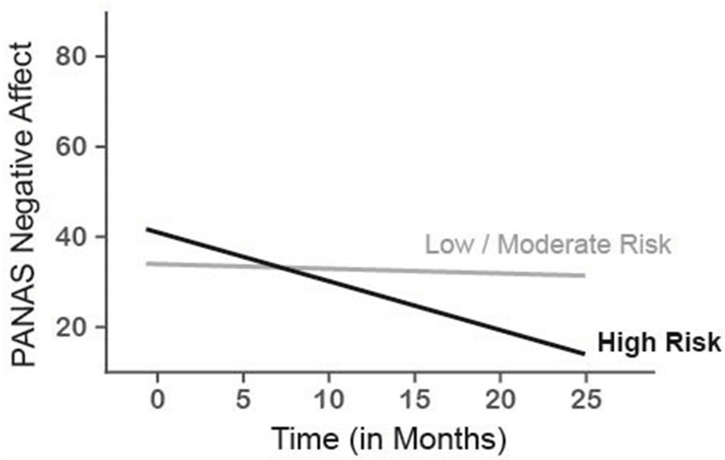
‡$p = 0.073$

Model 5 (Table 7; random intercept and random slope where scores were allowed to vary across both time and participants) showed that participants in the high risk category demonstrated slopes over time that differed from other participants (b = -0.98, SE = 0.55, χ^2 Δ = 3.19, p = 0.073). Although not statistically significant, this result indicated that amongst the high recidivism risk participants, PANAS Negative Affect Total scores demonstrated greater decreases across time than amongst participants in the low and moderate recidivism risk categories. The magnitude of this decrease was such that, with every additional month after the start of their probation, the higher recidivism risk category participants reported approximately one point lower on the PANAS Negative Affect Total scale than the participants in the moderate and low risk categories over the same time period.

A graphical representation of the difference in PANAS Negative Affect Total slopes over time for high versus low-to-moderate recidivism risk participants is provided in Figure 1 below. As seen in Figure 1, PANAS Negative Affect Total did not demonstrate a statistically significant change over time in the low-to-moderate recidivism risk group; however, a visible overall reduction in PANAS Negative Affect Total was near statistically significant in the high recidivism risk participant group.

Figure 1

Simple Slopes Derived from a Multilevel Model (Table 7, Model 5) Depicting PANAS Negative Affect Total Across Time for High vs. Low-to-Moderate Recidivism Risk Category Participants



PANAS Negative Affect = Negative affect subscale of the Positive Affect Negative Affect Scale; Low / Moderate Risk slope, $p = 0.31$; High Risk slope, $p = 0.04$

Cox regression survival analyses

The PANAS Negative Affect Total subscale was further examined using Cox

Regression survival analyses (with time-varying predictors), which predicts recidivism outcome while also accounting for the timing when predictors were assessed and the timing of recidivism outcomes. This type of exploratory analysis of PANAS Negative Affect Total was considered important to determine if PANAS Negative Affect Total would emerge as significant dynamic predictors of recidivism for this sample of adults on probation. Additionally, the static variable of participants' recidivism risk category was added to Cox regression models to further explore whether PANAS Negative Affect Total predicts recidivism after accounting for risk for recidivism, as assessed by validated risk of recidivism tools.

Table 9

Cox Regression Survival Analysis (With Time-Varying Predictors) Hazard Ratios From Models Using PANAS Negative Affect Total and Recidivism Risk Category to Predict Recidivism Outcomes

Variable	*B*(*SE*)	exp (*B*) [95%CI]	*z*	*p*-value
Model 1 (*N* = 561 assessments from 310 individuals; 52 recidivism events)				
PANAS Negative Affect Total	0.021 (0.0086)	1.02 [1.00, 1.04]	2.45	0.014*
Model Fit				
Wald test / Concordance	6 (*df* = 1, *p* = 0.01) / 0.58			
Model 2 (*N* = 489 assessments from 263 individuals; 46 recidivism events)				
PANAS Negative Affect Total	0.013(0.010)	1.01 [0.99, 1.03]	1.24	0.21
Risk Score Category = Low (Reference = High)	-2.591(0.631)	0.07 [0.02, 0.26]	-4.10	<0.001***
Risk Score Category = Moderate (Reference = High)	-0.915(0.317)	0.40 [0.22, 0.75]	-2.89	0.004**
Model Fit				
Wald test / Concordance	21.83 (*df* = 3, *p*< 0.001) / 0.67			
Model 3 (*N* = 489 assessments from 263 individuals; 46 recidivism events)				
PANAS Negative Affect Total	0.005 (0.013)	1.01 [0.98, 1.03]	0.40	0.69
Risk Score Category = High	0.362 (0.836)	1.44 [0.28, 7.40]	0.43	0.66
PANAS Negative Affect Total * Risk Score Category = High	0.024 (0.020)	1.02 [0.98, 1.06]	1.19	0.23
Model Fit				
Wald test / Concordance	23.89 (*df* = 3, *p*< 0.001) / 0.61			

p* < .05; ***p* < .001, * *p* < .0001

Table 8 presents the Cox regression models using PANAS Negative Affect Total and recidivism risk category to predict recidivism outcomes. Model 1 showed that PANAS Negative Affect Total was positively and significantly related to recidivism outcomes (B = 0.021, SE = 0.0086, p = 0.014). Exponentiating the coefficient to gain a hazard ratio (exp (B) = 1.02, 95% CI = 1.00, 1.04) revealed that for every 1 point increase in PANAS Negative Affect Total scale, participants were 2% more likely to recidivate in the time period subsequent to that assessment.

In Model 2, risk of recidivism was added in a categorical way (with higher risk as a

reference category) to the Cox regression model, with both low (B = -2.591, SE = 0.631; exp (B) = 0.07, 95% CI = 0.02, 0.26, $p < 0.001$) and moderate risk categories (B = -0.915, SE = 0.317; exp (B) = 0.40, 95% CI = 0.02, 0.26, p = 0.004) being inverse significant predictors of recidivism outcomes in the expected manner: participants in the low recidivism risk category scores were 93% less likely to recidivate compared to those in the high category risk, while participants in the moderate risk category scores were 60% less likely to recidivate compared to those in the high category risk. However, PANAS Negative Affect Total was not a significant independent predictor, demonstrating that PANAS Negative Affect Total is not a significant predictor of recidivism outcomes after accounting for the participants' recidivism risk category.

In Model 3, we sought to explore whether the interaction between PANAS Negative Affect Total and the high recidivism risk category created a compounding effect, such that those with high risk of recidivism who also reported high PANAS Negative Affect Total would be at a significantly higher risk of recidivism. The Model 3 results demonstrated that the interaction between high risk and PANAS Negative Affect Total was not a significant predictor of recidivism outcomes.

Overall, Cox regression results for PANAS Negative Affect Total demonstrated that, although PANAS Negative Affect Total was a significant predictor of recidivism outcomes when modelled on its own in Model 1 (Table 8), this effect disappeared when participants' recidivism risk categories were added in subsequent models, such that participants' recidivism risk categories adequately accounted for any independent predictive power that PANAS Negative Affect Total demonstrated in Model 1.

PANAS Negative Affect - High Activation

Multilevel modelling

The PANAS Negative Affect High Activation subscale was examined using multilevel modelling (MLM) analyses, to explore if any potential change-over-time patterns occurred for PANAS Negative Affect High Activation scale for the study adult probation sample. This type of exploratory analysis was considered important to determine if and how negative affect that is high in behavioural activation (e.g., angry, ashamed, guilty, irritable) might fluctuate for adults on supervision over time. Additionally, multilevel modelling was further utilised to explore if individual's age at start of supervision, their gender, or recidivism risk category status was related to the degree of high behavioural activation negative affect change over time for this participant cohort.

Table 9 below outlines the exploratory MLM results for PANAS Negative Affect High Activation scale. In Model 1, the intercept value displayed in Column 2 (b = 13.14, SE = 0.35) represents the average PANAS Negative Affect High Activation score for the study participants across the entire sample (i.e., when individual scores across different participants and different time points were all taken into consideration). To place this average sample score into a context, the PANAS Negative Affect High Activation scores can generally range from 7 to 35 (see Table 5; the scale has a total of 7 items rated on a Likert scale from 1-5). Furthermore, Model 1 also shows the Intraclass Correlation Coefficient (ICC) value, a descriptive statistic which explains how much variance in the intercept score is due to the person, and how much of the intercept variance is due to external circumstances (i.e., different assessment times). In Model 1, the ICC score of 0.50 indicated that 50% of the total variance in PANAS Negative Affect High Activation scores can be attributed to similarities in scores for the same participant across time, while 50% of total variance can be attributed to differences across multiple assessments over time.

Model 2 (Table 9, random intercept, fixed slope) was subsequently used to examine whether the sample average on the PANAS Negative Affect High Activation scores would change significantly over time; this model was not significant, showing the sample, on average, did not demonstrate change in scores through time.

Furthermore, in Model 3 (Table 9, random intercept, random slope), where scores were allowed to change at different rates and in different directions (e.g., positive versus negative) for each participant, the average PANAS Negative Affect High Activation score change over time also remained non-significant. However, the Chi Square analysis of the difference between the Models 2 and 3 was statistically significant, with Model 3 providing a statistically significantly better fit to the data compared to Model 2. This better model-to-data fit result indicated that PANAS Negative Affect High Activation slopes might be significantly changing over time for some of the sample participants; however, the sample's PANAS Negative Affect High Activation average slope over time remained non-significant.

Table 10

Multilevel Model Unstandardized Coefficients Predicting PANAS Negative Affect High Activation Across Multiple Assessments (Minimum of 2, Maximum of 4) and Examining Longitudinal Growth Across Time and Interaction Between Time and Age, and Interaction with Time and Gender Using Restricted Maximum Likelihood Estimation

Variable	Random Intercept	Random Intercept and Fixed Slope	Random Intercept and Random Slope				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Fixed Effects							
Mean Negative Affect Total							
Intercept	13.14 (0.35)	13.14 (0.35)	13.15 (0.35)	13.16 (0.35)	13.16 (0.39)	12.96 (0.39)	12.96 (0.39)
Age at Release	-	-	-	-0.054 (0.029)	-0.05 (0.029)	-	-
Gender (Female)	-	-	-	-	-	0.86 (0.84)	0.86 (0.84)
Linear Slope							
Time in Months	-	-0.008 (0.038)	-0.018 (0.044)	-0.018 (0.044)	-0.018 (0.044)	-0.019 (0.047)	-0.021 (0.051)
Age at Release	-	-	-	-	-0.0034 (0.0037)	-	-
Gender (Female)	-	-	-	-	-	-	0.0064 (0.11)
Random Effects							
Variance Components							
Level 1 (residual)	15.28	15.40	12.72	12.79	12.69	12.70	12.68
Level 2 (intercept)	15.43	15.34	16.34	15.96	16.05	16.30	16.33
Level 2 (time)	-	-	0.075	0.074	0.077	0.076	0.079
Model Fit							
AIC	2739.8	2741.8	2739.5	2738.0	2739.1	2740.4	2769.2
BIC	2752.2	2758.2	2764.2	2766.7	2772.0	2742.4	2775.3
ICC	ICC = 0.50	-	-	-	-	-	-
χ^2 Δ from prior model	-	χ^2 Δ = 0.048	χ^2 Δ = 6.27*	χ^2 Δ = 3.55‡	χ^2 Δ = 0.89	χ^2 Δ = 1.078	χ^2 Δ = 0.0036

Note. $N = 451$ assessments from 182 individuals

*$p < .05$; **$p < .001$, ***$p < .0001$

‡$p = 0.059$

In Model 4 (Table 10; random intercepts and random slopes), participant age at start of probation was added to MLM in order to explore whether older versus younger participants reported higher or lower levels of PANAS Negative Affect High Activation.

Table 9 shows that the age estimate for Model 4 was nearly statistically significant (b = -0.054, SE = 0.029, $\chi^2 \Delta$ = 3.55, p = 0.059), indicating that older participants had on average reported nearly significantly lower PANAS Negative Affect High Activation scores than younger participants. However, although this result was near statistically significant, it was also very slight, such that for every year of their increased age, older participants were likely to report only 5% of a point lower PANAS Negative Affect High Activation score. In other words, the age difference between younger and older participants would have to amount to a minimum of twenty years before an average decrease of one point on the PANAS Negative Affect High Activation score for older participants would be observed.

In Model 5, we explored if there was an association between participant age and the magnitude or direction of their slopes across time, i.e., whether participants of different ages may generally show different degrees of change in PANAS Negative Affect High Activation across time. However, in Model 5, the age estimate was not statistically significant and did not assist understanding how individuals' PANAS Negative Affect High Activation scores change across time.

In Models 6 and 7 (Table 10; random intercepts and random slopes), participant gender (female) was added to the model to explore whether changes in PANAS Negative Affect High Activation over time was related to participant gender. Model 6 showed that, although female participants had on average scored 14% of a point lower on the PANAS Negative Affect High Activation scale, this decrease in average scores related to gender was not statistically significant, and therefore not meaningful with regards to any significant gender differences in PANAS Negative Affect High Activation scores.

Furthermore, examining whether average slopes tended to differ in female versus male groups in the sample, Model 7 was also not statistically significant. Overall, Models 6 and 7 (Table 10) demonstrated that participant gender is not a significant consideration in explaining the patterns of PANAS Negative Affect High Activation change over time for the study sample.

The next variable of exploratory interest in relation to examining the change of PANAS Negative Affect High Activation scores over time was the participants' risk of recidivism category. Notably, these multilevel models were run on a smaller sample due to a larger amount of missing information for the recidivism risk category, as compared to the participant age or gender information. As a result of a smaller sample, Models 1-3 were re-run in order to explore whether recidivism risk status was related to Negative Affect Total slopes within this smaller sample. Subsequently in Models 4 and 5, the high recidivism risk category was added to the multilevel modelling. The results of these analyses are presented in Table 11 below:

Table 11

Multilevel Model Unstandardized Coefficients Predicting PANAS Negative Affect High Activation Across Multiple Assessments (Minimum of 2, Maximum of 4) and Examining Longitudinal Growth Across Time and Interaction Between Time and Recidivism Risk Category Using Restricted Maximum Likelihood Estimation

Variable	Random Intercept	Random Intercept and Fixed Slope	Random Intercept and Random Slope		
	Model 1	Model 2	Model 3	Model 4	Model 5
Fixed Effects					
Mean Negative Affect Total					
Intercept	12.86 (0.35)	12.87 (0.35)	12.86 (0.35)	12.94 (0.37)	12.91 (0.37)
High Risk Status	-	-	-	-0.83 (1.16)	-1.008 (1.17)
Linear Slope					
Time in Months	-	-0.05 (0.04)	-0.06 (0.04)	-0.06 (0.04)	-0.04 (0.04)
High Risk Status	-	-	-	-	-0.37 (0.22)
Random Effects					
Variance Components					
Level 1 (residual)	14.56	14.56	13.99	13.96	13.97
Level 2 (intercept)	13.88	13.88	14.08	14.29	14.26
Level 2 (time)	-	-	-	0.02	0.014
Model Fit					
AIC	2381.9	2382.4	2384.6	2386.1	2385.3
BIC	2393.8	2398.3	2408.4	2413.9	2417.2
ICC	ICC = 0.50	-	-	-	-
χ^2 Δ from prior model	-	χ^2 Δ = 1.53	χ^2 Δ = 1.80	χ^2Δ =0.502	χ^2 Δ = 2.73‡

Note. *N* = 396 assessments from 161 individuals

p* < .05; ***p* < .001, * *p* < .0001

‡*p* = 0.098

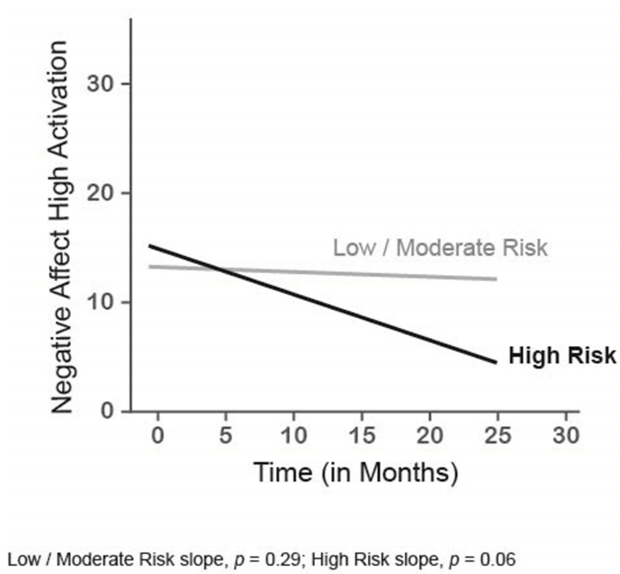
Model 5 (Table 11; random intercept and random slope, where scores were allowed to vary across both time and participants) showed that the high risk category demonstrated slopes over time that differed from other participants (*b* = -0.37, *SE* = 0.22, χ^2 *Δ* = 2.73, *p* = 0.098). Although not statistically significant, this result indicated that, amongst the high recidivism risk participants, PANAS Negative Affect High Activation scores demonstrated greater decreases across time than amongst participants in the low and moderate recidivism risk categories. The magnitude of this decrease was such that, with every additional month following the start of their probation, the higher recidivism risk category participants were likely to report approximately 1/3 (37%) of a point lower on PANAS Negative Affect High

Activation scale than the participants in the moderate and low risk categories over the same time period.

A graphical representation of the difference in PANAS Negative Affect High Activation slopes over time for high versus low-to-moderate recidivism risk participants is provided in Figure 2 below. As seen in Figure 2, PANAS Negative Affect High Activation did not demonstrate a statistically significant change over time in the low-to-moderate recidivism risk group; however, a visible overall reduction in PANAS Negative Affect High Activation was near statistically significant in the high recidivism risk participant group.

Figure 2

Simple Slopes Derived from a Multilevel Model (Table 10, Model 5) Depicting PANAS Negative Affect High Activation across Time for High vs. Low-to-Moderate Recidivism Risk Category Participants



Cox regression survival analyses

The PANAS Negative Affect High Activation subscale was further examined using Cox regression survival analyses (with time-varying predictors), which predicts recidivism outcome while also accounting for the timing when predictors were assessed and the timing of recidivism outcomes. This type of exploratory analysis of PANAS Negative Affect High Activation was considered important to determine if PANAS Negative Affect High Activation would emerge as a significant dynamic predictor of recidivism for this sample of adults on probation. Additionally, the static variable of participants' recidivism risk category was added to the Cox regression model to further explore whether PANAS Negative Affect High Activation predicts recidivism after accounting for risk for recidivism, as assessed by validated risk of recidivism tools.

Table 12

Cox Regression Survival Analysis (With Time-Varying Predictors) Hazard Ratios From Models Using PANAS Negative Affect High Activation and Recidivism Risk Category to Predict Recidivism Outcomes

Variable	*B*(*SE*)	exp (*B*) [95%CI]	*z*	*p*-value
Model 1 (*N* = 560 assessments from 309 individuals; 52 recidivism events)				
PANAS Negative Affect: High Activation	0.058 (0.020)	1.06 [1.02, 1.10]	2.79	0.005**
Model Fit				
Wald test / Concordance	7.8 (*df* = 1, *p* = 0.005) / 0.59			
Model 2 (*N* = 491 assessments from 264 individuals; 46 recidivism events)				
PANAS Negative Affect: High Activation	0.052 (0.023)	1.05 [1.01, 1.10]	2.23	0.025*
Risk Score Category = Low (Reference = High)	-2.649 (0.631)	0.07 [0.02, 0.24]	- 4.20	<0.001***
Risk Score Category = Moderate (Reference = High)	-0.934 (0.317)	0.39 [0.21, 0.73]	- 2.95	0.004**
Model Fit				
Wald test / Concordance	25.3 (*df* = 3, *p* < 0.001) / 0.69			
Model 3 (*N* = 491 assessments from 264 individuals; 46 recidivism events)				
PANAS Negative Affect: High Activation	0.029 (0.029)	1.03 [0.97, 0.97]	0.97	0.33
Risk Score Category = High	0.512 (0.777)	1.67 [0.36, 7.63]	0.66	0.51
PANAS Negative Affect: High Activation* Risk Score Category = High	0.053 (0.046)	1.05 [0.96, 1.15]	1.14	0.25
Model Fit				
Wald test / Concordance	27.33 (*df* = 3, *p* < 0.001) / 0.63			

*p < .05; **p < .001, ***p < .0001 (two-tailed)

Table 12 presents Cox regression models using PANAS Negative Affect High Activation and recidivism risk category to predict recidivism outcomes. Model 1 showed that PANAS Negative Affect High Activation was positively and significantly related to recidivism outcomes (B = 0.058, SE = 0.020, p < 0.001). Exponentiating the coefficient to gain a hazard ratio (exp (B) = 1.06, 95% CI = 1.02, 1.10) revealed that for every 1 point increase in PANAS Negative Affect High Activation scale, participants were 6% more likely to recidivate in the time period subsequent to that assessment.

In Model 2, risk of recidivism was added in a categorical way (with higher risk as a

reference category) to the Cox regression model, with both low (*B* = -2.649, *SE* = 0.631; exp (*B*) = 0.07, 95% CI = 0.02, 0.24, $p < 0.001$) and moderate risk categories (*B* = -0.934, *SE* = 0.317; exp (*B*) = 0.39, 95% CI = 0.21, 0.73, $p < 0.01$) being inverse significant predictors of recidivism outcomes in the expected manner: participants in the low recidivism risk category scores were 93% less likely to recidivate compared to those in the high category risk, while participants in the moderate risk category scores were 61% less likely to recidivate compared to those in the high category risk. However, PANAS Negative Affect High Activation also remained a significant independent predictor in this Model (*B* = 0.052, *SE* = 0.023; exp (*B*) = 1.05, 95% CI = 0.01, 1.10, $p < 0.05$), demonstrating that PANAS Negative Affect High Activation is a significant predictor of recidivism outcomes even after controlling for the participants' recidivism risk category, such that for every 1 point increase in PANAS Negative Affect High Activation scale, participants were 5% more likely to recidivate in the time period subsequent to that assessment.

In Model 3, we sought to explore whether the interaction between PANAS Negative Affect High Activation and the high recidivism risk category created a compounding effect, such that those with high risk of recidivism who also reported high PANAS Negative Affect High Activation, would be at a significantly higher risk of recidivism. The Model 3 results demonstrated that the interaction between high risk and PANAS Negative Affect High Activation was not a significant predictor of recidivism outcomes.

Overall, Cox regression results for PANAS Negative Affect High Activation demonstrated that negative affect that is high in behavioural activation (e.g., feeling angry, ashamed, guilty, irritable) was a significant predictor of recidivism outcomes when modelled on its own in Model 1 (Table 12), as well as remaining significant even after accounting for the predictive power of participants' recidivism risk category (Model 2), such that for every 1 point increase in PANAS Negative Affect High Activation scale, participants were 5% more likely to recidivate in the time period subsequent to that assessment, even after controlling for participants' recidivism risk category.

PANAS Negative Affect – Low Activation

Multilevel modelling

The PANAS Negative Affect Low Activation subscale was examined using multilevel modelling (MLM) analyses, to explore if any potential change-over-time patterns existed for PANAS Negative Affect Low Activation scale for the study adult probation sample. This type of exploratory analysis was considered important to determine if and how negative affect low in behavioural activation (e.g., depressed, tired, numb, bored) might fluctuate for adults on supervision over time. Additionally, multilevel modelling was further utilised to explore if individual's age at start of supervision, their gender, or recidivism risk category status had any relationship with the degree of low behavioural activation negative affect change over time for this participant cohort.

Table 13 below outlines the exploratory MLM results for PANAS Negative Affect Low Activation scale. In Model 1, the intercept value displayed in Column 2 (b = 20.93, SE = 0.58) represents the average PANAS Negative Affect Low Activation score for the study participants across the entire sample (i.e., when individual scores across different participants and different time points were all taken into consideration). To place this average sample score into a context, the PANAS Negative Affect Low Activation scores can range from 11 to 55 (see Table 5; the scale has a total of 11 items rated on a Likert scale from 1-5). Furthermore, Model 1 also shows the Intraclass Correlation Coefficient (ICC) value, a descriptive statistic which indicates how much of the intercept score variance is due to the person, and how much of the intercept variance is due to external circumstances (such as different assessment times). In Model 1, the ICC score of 0.57 indicated that 57% of the total variance in PANAS Negative Affect Low Activation scores can be attributed to similarities in scores for the same participant across time, while 43% of total variance can be attributed to the differences in assessment scores over time within the same person.

Model 2 (Table 13, random intercept, fixed slope) was subsequently used to examine whether the sample average on the PANAS Negative Affect Low Activation scores would change significantly over time; this model was not significant, showing the sample, on average, did not demonstrate change in scores through time.

Furthermore, in Model 3 (Table 13, random intercept, random slope), where participants' scores were allowed to change at different rates and in different directions (e.g., positive versus negative), the average PANAS Negative Affect Low Activation score change over time also remained non-significant. However, the Chi Square analysis of the difference between the Models 2 and 3 was statistically significant with Model 3 providing a statistically significantly better fit to the data compared to Model 2. This better model-to-data fit result indicated that PANAS Negative Affect Low Activation slopes might be significantly changing over time for some of the sample participants; however, the sample's PANAS Negative Affect Low Activation average slope change over time remained non-significant.

Table 13

Multilevel Model Unstandardized Coefficients Predicting PANAS Negative Affect Low Activation Across Multiple Assessments (Minimum of 2, Maximum of 4) and Examining Longitudinal Growth Across Time and Interaction Between Time and Age, and Interaction with Time and Gender Using Restricted Maximum Likelihood Estimation

Variable	Random Intercept	Random Intercept and Fixed Slope	Random Intercept and Random Slope				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Fixed Effects							
Mean Negative Affect Total							
Intercept	20.93 (0.58)	20.93 (0.58)	20.93 (0.58)	20.95 (0.57)	20.96 (0.57)	20.63 (0.66)	20.64 (0.66)
Age at Release	-	-	-	-0.127 (0.05)	-0.17 (0.048)	-	-
Gender (Female)	-	-	-	-	-	1.35 (1.39)	1.36 (1.40)
Linear Slope							
Time in Months	-	0.007 (0.058)	-0.026 (0.07)	-0.026 (0.070)	-0.026 (0.071)	-0.027 (0.071)	-0.025 (0.081)
Age at Release	-	-	-	-	-0.00025 (0.0058)	-	-
Gender (Female)	-	-	-	-	-	-	-0.0098 (0.17)
Random Effects							
Variance Components							
Level 1 (residual)	34.44	34.54	26.68	26.73	26.70	26.63	26.59
Level 2 (intercept)	46.65	46.67	48.92	46.67	46.71	48.92	48.99
Level 2 (time)	-	-	0.239	0.24	0.25	0.24	0.25
Model Fit							
AIC	3132.1	3134.1	3126.8	3121.7	3123.7	3127.8	3129.8
BIC	3144.4	3150.5	3151.4	3150.5	3156.6	3156.6	3162.7
ICC	ICC = 0.57	-	-	-	-	-	-
χ^2 Δ from prior model	-	χ^2 Δ = 0.015	χ^2 Δ = 11.28**	χ^2 Δ = 7.03**	χ^2 Δ = 0.015	χ^2 Δ = 0.94	χ^2 Δ = 0.004

Note. N = 449 assessments from 182 individuals

*$p < .05$; **$p < .001$, *** $p < .0001$

In Model 4 (Table 13; random intercepts and random slopes), participant age at start of probation was added to MLM in order to explore whether older versus younger participants reported higher or lower levels of PANAS Negative Affect Low Activation. Table 13 shows that the age estimate for Model 4 was statistically significant (b = -0.127, SE = 0.05, $\chi^2\ \Delta$ = 7.03, $p < .001$), indicating that older participants had on average reported statistically significantly lower PANAS Negative Affect Low Activation scores than the younger participants. However, although this result was statistically significant, it was also relatively slight, such that for every year of increased age, older participants were likely to report 13% of a point lower PANAS Negative Affect Low Activation score. In other words, the age difference between younger and older participants would have to amount to a minimum of 7.6 years before an average decrease of one point on the PANAS Negative Affect Low Activation score for older participants would be observed.

In Model 5, we explored if there was an association between participant age and the magnitude or direction of their slope across time, i.e., whether participants of different ages may generally show different degrees of change in PANAS Negative Affect Low Activation across time. However, in Model 5, the age estimate was not statistically significant and did not assist in understanding how individuals' PANAS Negative Affect Low Activation scores change across time.

In Models 6 and 7 (Table 13; random intercepts and random slopes), participant gender (female) was added to the model to explore whether changes in PANAS Negative Affect Low Activation over time were related to participant gender. Model 6 showed that, although female participants had on average scored 35% of a point higher on the PANAS Negative Affect Low Activation scale, this increase in average scores related to gender was not statistically significant, and therefore not meaningful with regards to any significant gender differences in PANAS Negative Affect Low Activation scores. Furthermore, examining whether average slopes tended to differ in female versus male groups in the sample, Model 7 was also not statistically significant. Overall, Models 6 and 7 (Table 6) demonstrated that participant gender is not a significant consideration in explaining the patterns of PANAS Negative Affect Low Activation change over time for the study sample.

The next variable of exploratory interest in relation to examining the change of

PANAS Negative Affect Low Activation scores over time was the participants' risk of recidivism category. Notably, these multilevel models were run on a smaller sample due to a larger amount of missing information for the recidivism risk category, as compared to the participant age or gender information. As a result of a smaller sample, Models 1-3 were re-run in order to explore whether recidivism risk status was related to Negative Affect Low Activation slopes within this smaller sample. Subsequently in Models 4 and 5, the high recidivism risk category was added to the multilevel modelling. The results of these analyses are presented in Table 14 below:

Table 14

Multilevel Model Unstandardized Coefficients Predicting PANAS Negative Affect Low Activation Across Multiple Assessments (Minimum of 2, Maximum of 4) and Examining Longitudinal Growth Across Time and Interaction Between Time and Recidivism Risk Category Using Restricted Maximum Likelihood Estimation

Variable	Random Intercept	Random Intercept and Fixed Slope	Random Intercept and Random Slope		
	Model 1	Model 2	Model 3	Model 4	Model 5
Fixed Effects					
Mean Negative Affect Total					
Intercept	20.46 (0.59)	20.49 (0.59)	20.47 (0.59)	20.33 (0.62)	20.28 (0.62)
High Risk Status	-	-	-	1.46 (1.87)	1.15 (1.88)
Linear Slope					
Time in Months	-	-0.068 (0.061)	-0.085 (0.064)	-0.082 (0.064)	-0.056 (0.064)
High Risk Status	-	-	-	-	-0.611 (0.353)
Random Effects					
Variance Components					
Level 1 (residual)	31.03	31.12	29.40	29.56	30.02
Level 2 (intercept)	43.50	43.11	43.23	43.09	42.37
Level 2 (time)	-	-	-	0.06	0.042
Model Fit					
AIC	2712.9	2713.6	2716.2	2717.6	2716.6
BIC	2724.8	2729.5	2740.1	2745.4	2748.4
ICC	ICC = 0.57	-	-	-	-
χ^2 Δ from prior model	-	χ^2 Δ = 1.25	χ^2 Δ = 1.39	χ^2Δ =0.59	χ^2 Δ = 3.00‡

Note. N = 394 assessments from 161 individuals

*$p < .05$; **$p < .001$, *** $p < .0001$

‡$p = 0.083$

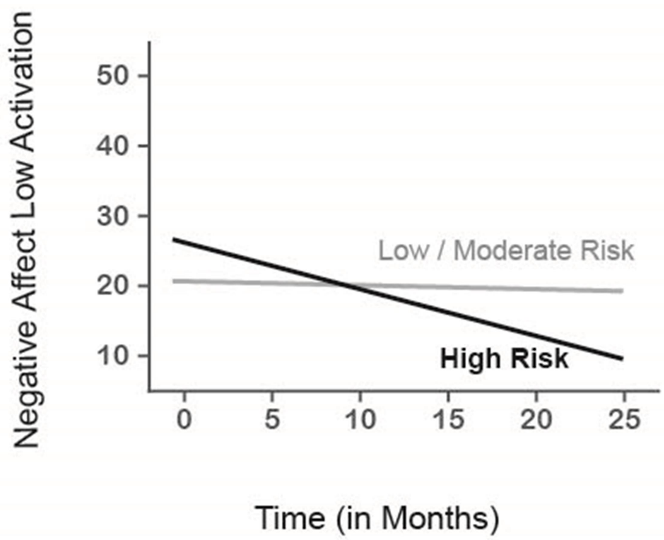
Model 5 (Table 14; random intercept and random slope where scores were allowed to vary across both time and participants) showed that participants in the high risk category demonstrated slopes over time that differed from other participants (b = -0.61, SE = 0.35, χ^2 Δ = 3.00, p = 0.083). Although not statistically significant, this result indicated that amongst the high recidivism risk participants, PANAS Negative Affect Low Activation scores demonstrated greater decreases across time than amongst participants in the low and moderate recidivism risk categories. The magnitude of this decrease was such that, with every additional month after the start of their probation, the higher recidivism risk category participants were likely to report approximately 2/3 (61%) of a point lower on PANAS

Negative Affect Low Activation scale than the participants in the moderate and low risk categories over the same time period.

A graphical representation of the difference in PANAS Negative Affect Low Activation slopes over time for high versus low-to-moderate recidivism risk participants is provided in Figure 3 below. As seen in Figure 3, and consistent with the previous negative affect scales analyses, PANAS Negative Affect Low Activation did not demonstrate statistically significant change over time in the low-to-moderate recidivism risk group; however, a visible overall reduction in PANAS Negative Affect Low Activation over time was near statistically significant in the high recidivism risk participant group.

Figure 3

Simple Slopes Derived from a Multilevel Model (Table 13, Model 5) Depicting PANAS Negative Affect Low Activation across Time for High vs. Low-to-Moderate Recidivism Risk Category Participants



Low / Moderate Risk slope, $p = 0.39$; High Risk slope, $p = 0.05$

Cox regression survival analyses

The PANAS Negative Affect Low Activation subscale was further examined using Cox Regression survival analyses (with time-varying predictors), which predicts recidivism outcome while also accounting for the timing when predictors were assessed and the timing of recidivism outcomes. This type of exploratory analysis of PANAS Negative Affect Low Activation was considered important to determine if PANAS Negative Affect Low Activation would emerge as a significant dynamic predictor of recidivism for this sample of adults on probation. Additionally, the static variable of participants' recidivism risk category was added to Cox regression models to further explore whether PANAS Negative Affect Low Activation predicted recidivism after accounting for risk for recidivism, as assessed by validated risk of recidivism tools.

Table 15

Cox Regression Survival Analysis (With Time-Varying Predictors) Hazard Ratios From Models Using PANAS Negative Affect Low Activation and Recidivism Risk Category to Predict Recidivism Outcomes

Variable	*B*(*SE*)	exp (*B*) [95%CI]	*z*	*p*-value
Model 1 (*N* = 560 assessments from 309 individuals; 52 recidivism events)				
PANAS Negative Affect: Low Activation	0.028 (0.014)	1.03 [1.00, 1.05]	2.02	0.044*
Model Fit				
Wald test / Concordance	4.06 (*df* = 1, *p* = 0.04) / 0.56			
Model 2 (*N* = 488 assessments from 262 individuals; 46 recidivism events)				
PANAS Negative Affect: Low Activation	0.008 (0.017)	1.01 [0.97, 1.04]	0.50	0.62
Risk Score Category = Low (Reference = High)	-2.601 (0.633)	0.07 [0.02, 0.26]	-4.11	<0.001***
Risk Score Category = Moderate (Reference = High)	-0.916 (0.399)	0.39 [0.21, 0.74]	-2.89	0.004**
Model Fit				
Wald test / Concordance	20.55 (*df* = 3, *p* < 0.001) / 0.66			
Model 3 (*N* = 488 assessments from 262 individuals; 46 recidivism events)				
PANAS Negative Affect: Low Activation	-0.003 (0.022)	1.00 [0.96, 1.04]	-0.012	0.95
Risk Score Category = High	0.412 (0.847)	1.51 [0.29, 7.95]	0.49	0.63
PANAS Negative Affect: Low Activation* Risk Score Category = High	0.037 (0.034)	1.03 [0.97, 1.10]	1.10	0.27
Model Fit				
Wald test / Concordance	21.15 (*df* = 3, *p* < 0.001) / 0.63			

p* < .05; ***p* < .001, * *p* < .0001 (two-tailed)

Table 15 presents Cox regression models using PANAS Negative Affect Low Activation and recidivism risk category to predict recidivism outcomes. Model 1 showed that PANAS Negative Affect Low Activation was positively and significantly related to recidivism outcomes (B = 0.028, SE = 0.014, p < 0.05). Exponentiating the coefficient to gain a hazard ratio (exp (B) = 1.03, 95% CI = 1.00, 1.05) revealed that for every 1 point increase in PANAS Negative Affect Low Activation scale, participants were 3% more likely to recidivate in the time period subsequent to that assessment.

In Model 2, risk of recidivism was added in a categorical way (with higher risk as a

reference category) to the Cox regression model, with both low (*B* = -2.601, *SE* = 0.633; exp (*B*) = 0.07, 95% CI = 0.02, 0.26, $p < 0.001$) and moderate risk categories (*B* = -0.916, *SE* = 0.399; exp (*B*) = 0.39, 95% CI = 0.21, 0.74, $p < 0.01$) being inverse significant predictors of recidivism outcomes in the expected manner: participants in the low recidivism risk category scores were 93% less likely to recidivate compared to those in the high category risk, while participants in the moderate risk category scores were 61% less likely to recidivate compared to those in the high category risk. However, PANAS Negative Affect Low Activation was not a significant independent predictor, demonstrating that PANAS Negative Affect Low Activation is not a significant predictor of recidivism outcomes after accounting for participants' recidivism risk category.

In Model 3, we sought to explore whether the interaction between PANAS Negative Affect Low Activation and the high recidivism risk category created a compounding effect, such that those with high risk of recidivism who also reported high PANAS Negative Affect Low Activation would be at a significantly higher risk of recidivism. The Model 3 results demonstrated that the interaction between high risk and PANAS Negative Affect Low Activation was not a significant predictor of recidivism outcomes.

Overall, Cox regression results for PANAS Negative Affect Low Activation demonstrated that, although PANAS Negative Affect Low Activation was a significant predictor of recidivism outcomes when modelled on its own in Model 1 (Table 15), this effect disappeared when participants' risk categories were added in subsequent models, such that participants' recidivism risk categories adequately accounted for any independent predictive power that PANAS Negative Affect Low Activation has demonstrated in Model 1.

PANAS Positive Affect - Total

Multilevel modelling

The PANAS Positive Affect Total subscale was examined using multilevel modelling (MLM) analyses, to explore if any potential change-over-time pattern exists for PANAS Positive Affect Total scale for the study adult probation sample. This type of exploratory analysis was considered important to determine if and how the PANAS Positive Affect Total might fluctuate for adults on supervision over time. Additionally, multilevel modelling was further utilised to explore whether individuals' age at start of supervision, their gender, or recidivism risk category status have any relationship with the degree of total positive affect change over time for this participant cohort.

Table 16 below outlines the exploratory MLM results for PANAS Positive Affect Total scale. In Model 1, the intercept value displayed in Column 2 (b = 41.53, SE = 0.68) represents the average PANAS Positive Affect Total score for the study participants across the entire sample (i.e., when individual scores across different participants and different time points were all taken into consideration). To place this average sample score into a context, the PANAS Positive Affect Total scores can can range from 12 to 60 (see Table 5; the scale has a total of 12 items rated on a Likert scale from 1-5). Furthermore, Model 1 also shows the Intraclass Correlation Coefficient (ICC) value, a descriptive statistic which indicates how much of the intercept score variance is due to the person, and how much of the intercept variance is due to external circumstances (such as different assessment times). In Model 1, the ICC score of 0.52 indicated that 52% of the total variance in PANAS Positive Affect Total scores can be attributed to similarities in scores for the same participant across time, while 48% of total variance can be attributed to differences in assessment scores over time within the same person.

Model 2 (Table 16, random intercept, fixed slope) was subsequently used to examine whether the sample average on the PANAS Positive Affect Total scores would change significantly over time; this model was not significant, showing the sample, on average, did not demonstrate change in scores through time.

In Model 3 (Table 16, random intercept, random slope), where participants' scores were allowed to change at different rates and in different directions (e.g., positive versus negative) for each participant, both the average PANAS Positive Affect Total score change over time and change in overall model fit (Chi square) remained non-significant. This indicates that all sample participants generally followed the full sample trend, i.e., no statistically significant change in PANAS Positive Affect Total over time.

In Model 4 (Table 16; random intercepts and random slopes), participant age at start of probation was added to MLM to explore whether older versus younger participants reported significantly higher or lower levels of PANAS Positive Affect Total; this model was also not significant.

Table 16

Multilevel Model Unstandardized Coefficients Predicting PANAS Positive Affect Total Across Multiple Assessments (Minimum of 2, Maximum of 4) and Examining Longitudinal Growth Across Time and Interaction Between Time and Age, and Interaction with Time and Gender Using Restricted Maximum Likelihood Estimation

Variable	Random Intercept	Random Intercept and Fixed Slope	Random Intercept and Random Slope				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Fixed Effects							
Mean Negative Affect Total							
Intercept	41.53 (0.68)	41.56 (0.68)	41.59 (0.68)	41.59 (0.68)	41.58 (0.68)	41.83 (0.78)	41.84 (0.77)
Age at Release	-	-	-	0.056 (0.057)	0.054 (0.057)	-	-
Gender (Female)	-	-	-	-	-	-1.03 (1.64)	-1.16 (1.65)
Linear Slope							
Time in Months	-	-0.065 (0.072)	-0.036 (0.082)	-0.036 (0.082)	-0.037 (0.082)	-0.035 (0.082)	-0.067 (0.094)
Age at Release	-	-	-	-	0.0039 (0.0068)	-	-
Gender (Female)	-	-	-	-	-	-	0.143 (0.19)
Random Effects							
Variance Components							
Level 1 (residual)	55.77	55.68	48.98	48.99	49.04	48.96	48.87
Level 2 (intercept)	60.61	60.96	62.72	62.72	62.76	62.95	62.89
Level 2 (time)	-	-	0.191	0.191	0.19	0.19	0.20
Model Fit							
AIC	3326.1	3327.3	3327.0	3328.0	3329.7	3328.6	3330.1
BIC	3338.5	3343.8	3351.7	3356.8	3362.6	3357.4	3362.9
ICC	ICC = 0.52	-	-	-	-	-	-
χ^2 Δ from prior model	-	χ^2 Δ = 0.79	χ^2 Δ = 4.32	χ^2 Δ = 0.97	χ^2 Δ = 0.033	χ^2 Δ = 0.39	χ^2 Δ = 0.54

Note. N = 450 assessments from 182 individuals

*$p < .05$; **$p < .001$, ***$p < .0001$

In Model 5, we explored if there was an association between participant age and the magnitude or direction of their slope across time, i.e., whether participants of different ages may generally show different degrees of change in PANAS Positive Affect Total across time.

Again, in Model 5, the age estimate was not statistically significant in terms of assisting to understand how individuals' PANAS Positive Affect Total scores change across time. Overall, Models 4 and 5 (Table 16) demonstrated that participant age was not a significant consideration in explaining the patterns of PANAS Positive Affect Total change over time for the study sample.

In Model 6 (Table 16; random intercepts and random slopes), participant gender (female) was added to the model to explore whether changes in PANAS Positive Affect Total over time could be related to participant gender. Model 6 showed that, although female participants had on average scored one point lower on the PANAS Positive Affect Total scale, this reduction in average scores related to gender was not statistically significant, and therefore not meaningful with regards to any significant gender differences in PANAS Positive Affect Total scores. Furthermore, examining whether average slopes tended to differ in female versus male groups in the sample, Model 7 was also not statistically significant. Overall, Models 6 and 7 (Table 7) demonstrated that participant gender is not a significant consideration in explaining the patterns of PANAS Positive Affect Total change over time for the study sample.

The next variable of exploratory interest in relation to examining the change of PANAS Positive Affect Total scores over time was the participants' risk of recidivism category. Notably, these multilevel models were run on a smaller sample due to a larger amount of missing information for the recidivism risk category, as compared to the participant age or gender information. As a result of a smaller sample, Models 1-3 were re-run in order to explore whether recidivism risk status was related to Positive Affect Total slopes within this smaller sample. Subsequently in Models 4 and 5, the high recidivism risk category was added to the multilevel modelling. The results of these analyses are presented in

Table 17 below:

Table 17

Multilevel Model Unstandardized Coefficients Predicting PANAS Positive Affect Total Across Multiple Assessments (Minimum of 2, Maximum of 4) and Examining Longitudinal Growth Across Time and Interaction Between Time and Recidivism Risk Category Using Restricted Maximum Likelihood Estimation

Variable	Random Intercept	Random Intercept and Fixed Slope	Random Intercept and Random Slope		
	Model 1	Model 2	Model 3	Model 4	Model 5
Fixed Effects					
Mean Negative Affect Total					
Intercept	41.54 (0.70)	41.56 (0.70)	41.65 (0.70)	41.36 (0.74)	41.41(0.74)
High Risk Status	-	-	-	2.95 (2.30)	3.97 (2.31)
Linear Slope					
Time in Months	-	-0.080 (0.080)	-0.023(0.097)	-0.017 (0.096)	-0.081 (0.095)
High Risk Status	-	-	-	-	1.32 (0.46)
Random Effects					
Variance Components					
Level 1 (residual)	56.83	56.59	46.51	46.36	46.05
Level 2 (intercept)	55.23	55.84	57.47	58.14	57.89
Level 2 (time)	-	-	-	0.31	0.268
Model Fit					
AIC	2915.5	2916.6	2912.3	2912.7	2906.6
BIC	2927.5	2932.5	2936.2	2940.6	2938.4
ICC	ICC = 0.52	-	-	-	-
χ^2 Δ from prior model	-	χ^2 Δ = 0.98	χ^2 Δ = 8.23*	χ^2Δ =1.62	χ^2 Δ = 8.11**

Note. N = 395 assessments from 161 individuals

*p < .05; **p < .001, ***p < .0001

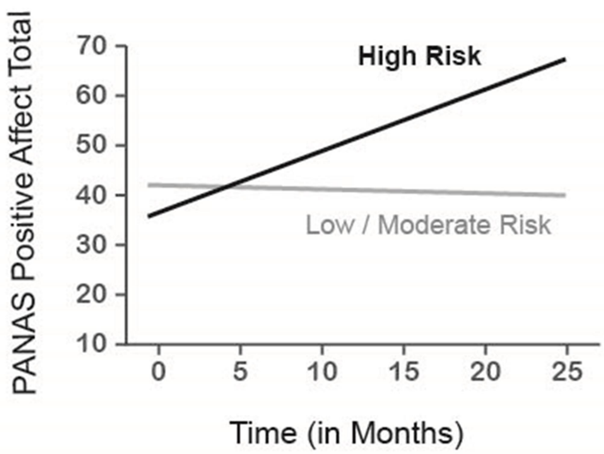
In Model 3 (Table 17, random intercept, random slope), where participants' scores were allowed to change at different rates and in different directions (e.g., positive versus negative) for each participant, the average PANAS Positive Affect Total score change over time remained non-significant. However, the Chi Square analysis of the difference between the Models 2 and 3 was statistically significant with Model 3 providing a statistically significantly better fit to data compared to Model 2. This better model-to-data fit result indicated that PANAS Positive Affect Total slopes might be significantly changing over time for some of the sample participants; however, the sample's PANAS Positive Affect Total average slope change over time remained non-significant.

Model 5 (Table 17; random intercept and random slope) showed that the high risk category estimate (where scores were allowed to vary across both time and participants) was statistically significant (b = 1.32, SE = 0.46, $\chi^2 \Delta$ = 8.11, p < 0.001). This result indicated that, amongst high recidivism risk participants, the increase in PANAS Positive Affect Total demonstrated greater rise across time than in the low and moderate recidivism risk categories, with this difference being statistically significant. The magnitude of this increase was such that, with every additional month after the start of their probation, the higher recidivism risk category participants were likely to report approximately 1.3 point higher on the PANAS Positive Affect Total scale than the participants in the moderate and low risk categories over the same time period.

A graphical representation of the difference in PANAS Positive Affect Total slopes over time for high versus low-to-moderate recidivism risk participants is provided in Figure 4 below. As seen in Figure 4, PANAS Positive Affect Total did not demonstrate a statistically significant change over time in the low-to-moderate recidivism risk group; however, a visible overall increase in PANAS Positive Affect Total over time was statistically significant in the high recidivism risk participant group.

Figure 4

Simple Slopes Derived from a Multilevel Model (Table 16, Model 5) Depicting PANAS Positive Affect Total across Time for High vs. Low-to-Moderate Recidivism Risk Category Participants



Low / Moderate Risk slope, p = 0.39; High Risk slope, p = 0.006

Cox regression survival analyses

The PANAS Positive Affect Total subscale was further examined using Cox Regression survival analyses (with time-varying predictors), which predicts recidivism outcome while also accounting for the timing when predictors were assessed and the timing of recidivism outcomes. This type of exploratory analysis of PANAS Positive Affect Total was considered important to determine if PANAS Positive Affect Total would emerge as significant dynamic predictor of recidivism for this sample of adults on probation. Additionally, the static variable of participants' recidivism risk category was added to Cox regression models to further explore whether PANAS Positive Affect Total predicts recidivism after accounting for risk for recidivism, as assessed by validated risk of recidivism tools.

Table 48

Cox Regression Survival Analysis (With Time-Varying Predictors) Hazard Ratios From Models Using PANAS Positive Affect Total and Recidivism Risk Category to Predict Recidivism Outcomes

Variable	*B*(*SE*)	exp(*B*) [95%CI]	*z*	*p*-value
Model 1 (*N* = 561 assessments from 310 individuals; 52 recidivism events)				
PANAS Positive Affect Total	-0.049 (0.013)	0.95 [0.93, 0.98]	-3.77	0.00017***
Model Fit				
Wald test / Concordance	14.19 (*df* = 1, *p* < 0.001) / 0.66			
Model 2 (*N* = 489 assessments from 263 individuals; 46 recidivism events)				
PANAS Positive Affect Total	-0.045 (0.014)	0.95 [0.93, 0.98]	-3.32	0.00089***
Risk Score Category = Low (Reference = High)	-2.680 (0.631)	0.06 [0.01, 0.23]	-4.24	<0.001***
Risk Score Category = Moderate (Reference = High)	-1.043 (0.319)	0.36 [0.19, 0.66]	-3.27	0.0011**
Model Fit				
Wald test / Concordance	30.94 (*df* = 3, *p* < 0.001) / 0.73			
Model 3 (*N* = 489 assessments from 263 individuals; 46 recidivism events)				
PANAS Positive Affect Total	-0.039 (0.017)	0.96 [0.92, 0.99]	-2.33	0.019*
Risk Score Category = High	2.22 (1.11)	9.25 [1.04, 82.23]	1.99	0.046*
PANAS Positive Affect Total * Risk Score Category = High	-0.022 (0.029)	0.97 [0.92, 1.03]	-0.77	0.44
Model Fit				
Wald test / Concordance	32.66 (*df* = 3, *p* < 0.001) / 0.68			

*p < .05; **p < .001, ***p < .0001 (two-tailed)

Table 18 presents Cox regression models using PANAS Positive Affect Total and recidivism risk category to predict recidivism outcomes. Model 1 showed that PANAS Positive Affect Total was significantly and inversely related to recidivism outcomes (B = -0.049, SE = 0.013, p < 0.0001). Exponentiating the coefficient to gain a hazard ratio (exp (B) = 0.95, 95% CI = 0.93, 0.98) revealed that for every 1 point increase in PANAS Positive Affect Total scale, participants were 5% less likely to recidivate in the time period subsequent to that assessment.

In Model 2, risk of recidivism was added in a categorical way (with higher risk as a reference category) to the Cox regression model, with both low (B = -2.680, SE = 0.631; exp (B) = 0.06, 95% CI = 0.01, 0.23, $p < 0.0001$) and moderate risk categories (B = -1.043, SE = 0.319; exp (B) = 0.36, 95% CI = 0.19, 0.66, $p < 0.001$) being inverse significant predictors of recidivism outcomes in the expected manner: participants in the low recidivism risk category scores were 94% less likely to recidivate compared to those in the high category risk, while participants in the moderate risk category scores were 64% less likely to recidivate compared to those in the high category risk. However, PANAS Positive Affect Total also remained a significant independent predictor in Model 2 (B = -0.045, SE = 0.014; exp (B) = 0.95, 95% CI = 0.93, 0.98, $p < 0.0001$), demonstrating that PANAS Positive Affect Total was a significant predictor of recidivism outcomes even after controlling for the participants' recidivism risk category, such that for every 1 point increase in PANAS Positive Affect Total scale, participants were 5% less likely to recidivate in the time period subsequent to that assessment while taking risk tool scores into account.

In Model 3, we sought to explore whether the interaction between PANAS Positive Affect Total and the high recidivism risk category created a compounding effect, such that those with high risk of recidivism who also reported higher PANAS Positive Affect Total would be at a significantly higher risk of recidivism. The Model 3 results demonstrated that the interaction between high risk and PANAS Positive Affect Total was not a significant predictor of recidivism outcomes.

Overall, the Cox regression results have demonstrated that PANAS Positive Affect Total was a significant predictor of recidivism outcomes when modelled on its own in Model 1 (Table 18), as well as remaining a significant predictor even after accounting for the predictive power of participants' recidivism risk category (Model 2), such that for every 1 point increase in PANAS Positive Affect Total scale, participants were 5% less likely to recidivate in the time period subsequent to that assessment. This result indicates that positive emotions, as measured by PANAS, remained significant predictors of recidivism outcomes even after accounting for participants' recidivism risk category.

PANAS Positive Affect – High Activation

Multilevel modelling

The PANAS Positive Affect High Activation subscale was examined using multilevel modelling (MLM) analyses, to explore if any potential change-over-time pattern exists for PANAS Positive Affect High Activation scale for the study adult probation sample. This type of exploratory analysis was considered important to determine if and how positive affect that is high in behavioural activation (e.g., feeling enthusiastic, excited, proud, strong) might fluctuate for adults on supervision over time. Additionally, multilevel modelling was utilised to explore if individuals' age at start of supervision, their gender, or recidivism risk category status have any relationship with the degree of high behavioural activation positive affect change over time for this participant cohort.

Table 19 below outlines the exploratory MLM results for PANAS Positive Affect High Activation subscale. In Model 1, the intercept value displayed in Column 2 (b = 24.43, SE = 0.39) represents the average PANAS Positive Affect High Activation score for the study participants across the entire sample (i.e., when individual scores across different participants and different time points were all taken into consideration). To place this average sample score into a context, the PANAS Positive Affect High Activation scores can range from 7 to 35 (see Table 6; the scale has a total of 7 items rated on a Likert scale from 1-5). Furthermore, Model 1 also shows the Intraclass Correlation Coefficient (ICC) value, a descriptive statistic which indicates how much of the intercept score variance is due to the person, and how much of the intercept variance is due to external circumstances (such as different assessment times). In Model 1, the ICC score of 0.46 indicated that 46% of the total variance in PANAS Positive Affect High Activation scores can be attributed to similarities in scores for the same participant across time, while 54% of total variance can be attributed to differences in assessment scores over time within the same person.

Model 2 (Table 19, random intercept, fixed slope) was subsequently used to examine whether the sample average on the PANAS Positive Affect High Activation scores would change significantly over time; this model was not significant, showing the sample, on average, did not demonstrate change in scores through time.

In Model 3 (Table 19, random intercept, random slope), where participants' scores were allowed to change at different rates and in different directions (e.g., positive versus negative) for each participant, both the average PANAS Positive Affect High Activation score change over time and the change in overall model fit (Chi square) remained non-significant.

In Model 4 (Table 19; random intercepts and random slopes), participant age at start of probation was added to the model to explore whether older versus younger participants reported higher or lower levels of PANAS Positive Affect High Activation; this model was also not significant.

Table 19

Multilevel Model Unstandardized Coefficients Predicting PANAS Positive Affect High Activation Across Multiple Assessments (Minimum of 2, Maximum of 4) and Examining Longitudinal Growth Across Time and Interaction Between Time and Age, and Interaction with Time and Gender Using Restricted Maximum Likelihood Estimation

Variable	Random Intercept	Random Intercept and Fixed Slope	Random Intercept and Random Slope				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Fixed Effects							
Mean Negative Affect Total							
Intercept	24.43 (0.39)	24.45 (0.39)	24.45 (0.39)	24.45 (0.39)	24.45 (0.39)	24.57 (0.45)	24.57 (0.44)
Age at Release	-	-	-	-0.00030 (0.033)	-0.00038 (0.033)	-	-
Gender (Female)	-	-	-	-	-	-0.51 (0.94)	-0.56 (0.95)
Linear Slope							
Time in Months	-	-0.042 (0.045)	-0.036 (0.049)	-0.036 (0.049)	-0.036 (0.049)	-0.035 (0.049)	-0.048 (0.057)
Age at Release	-	-	-	-	0.0021 (0.0041)	-	-
Gender (Female)	-	-	-	-	-	-	0.056 (0.95)
Random Effects							
Variance Components							
Level 1 (residual)	21.61	21.57	19.96	19.95	19.96	19.96	48.87
Level 2 (intercept)	18.71	18.85	19.19	19.34	19.36	19.27	62.89
Level 2 (time)	-	-	0.046	0.046	0.048	0.046	0.20
Model Fit							
AIC	2846.1	2847.2	2849.5	2851.5	2853.2	2851.2	2853.0
BIC	2858.4	2863.6	2874.1	2880.2	2886.0	2879.9	2885.8
ICC	ICC = 0.46	-	-	-	-	-	-
χ^2 Δ from prior model	-	χ^2 Δ = 0.89	χ^2 Δ = 1.71	χ^2 Δ = 0.0001	χ^2 Δ = 0.27	χ^2 Δ = 0.29	χ^2 Δ = 0.23

Note. N = 446 assessments from 182 individuals

*p < .05; **p < .001, ***p < .0001 (two-tailed)

In Model 5, we explored if there was an association between participant age and the magnitude or direction of their slope across time, i.e., whether participants of different ages may generally show different degrees of change in PANAS Positive Affect High Activation across time. Again, in Model 5, the age estimate was not statistically significant and did not assist in understanding how individuals' PANAS Positive Affect High Activation scores change across time. Overall, Models 4 and 5 (Table 19) demonstrated that participant age is not a significant consideration in explaining the patterns of PANAS Positive Affect High Activation change over time for the study sample.

In Model 6 (Table 19; random intercepts and random slopes), participant gender (female) was added into MLM in order to explore whether changes in PANAS Positive Affect High Activation over time could be related to participant gender. Model 6 showed that, although female participants had on average scored half a point lower on the PANAS Positive Affect High Activation scale, this reduction in average scores related to gender was not statistically significant, and therefore not meaningful with regards to any significant gender differences in PANAS Positive Affect High Activation scores. Furthermore, examining whether average slopes tended to differ in female versus male groups in the sample, Model 7 was also not statistically significant. Overall, Models 6 and 7 (Table 19) demonstrated that participant gender is not a significant consideration in explaining the patterns of PANAS Positive Affect High Activation score change over time for the study sample.

The next variable of exploratory interest in relation to examining the change of PANAS Positive Affect High Activation scores over time was the participants' risk of recidivism category. Notably, these multilevel models were run on a smaller sample due to a larger amount of missing information for the recidivism risk category, as compared to the participant age or gender information. As a result of a smaller sample, Models 1-3 were re-run in order to explore whether recidivism risk status was related to Positive Affect High Activation slopes within this smaller sample. Subsequently in Models 4 and 5, the high recidivism risk category was added to the multilevel modelling. The results of these analyses are presented in Table 20 below:

Table 20

Multilevel Model Unstandardized Coefficients Predicting PANAS Positive Affect High Activation Across Multiple Assessments (Minimum of 2, Maximum of 4) and Examining Longitudinal Growth Across Time and Interaction Between Time and Recidivism Risk Category Using Restricted Maximum Likelihood Estimation

Variable	Random Intercept	Random Intercept and Fixed Slope	Random Intercept and Random Slope		
	Model 1	Model 2	Model 3	Model 4	Model 5
Fixed Effects					
Mean Negative Affect Total					
Intercept	24.42 (0.41)	24.43 (0.41)	24.45 (0.41)	24.28 (0.43)	24.31 (0.43)
High Risk Status	-	-	-	1.84 (1.36)	2.28 (1.37)
Linear Slope					
Time in Months	-	-0.041 (0.050)	-0.022(0.058)	-0.017 (0.058)	-0.047 (0.058)
High Risk Status	-	-	-	-	0.63 (0.28)
Random Effects					
Variance Components					
Level 1 (residual)	22.39	22.33	19.35	19.26	19.27
Level 2 (intercept)	17.51	17.68	18.20	18.38	18.27
Level 2 (time)	-	-	-	0.094	0.082
Model Fit					
AIC	2511.6	2512.9	2512.2	2512.4	2509.4
BIC	2523.5	2528.8	2536.0	2540.2	2541.2
ICC	ICC = 0.46	-	-	-	-
χ^2 Δ from prior model	-	χ^2 Δ = 0.68	χ^2 Δ = 4.77‡	χ^2Δ =1.80	χ^2 Δ = 4.99*

Note. N = 393 assessments from 161 individuals

*$p < .05$; **$p < .001$, ***$p < .0001$ (two-tailed)

‡$p = 0.092$

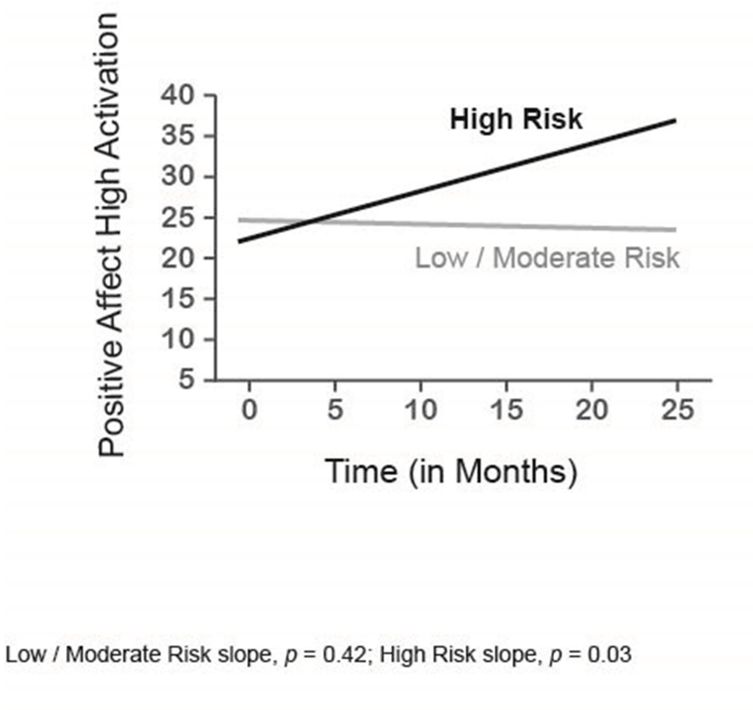
In Model 3 (Table 20, random intercept, random slope), where scores were allowed to change at different rates and in different directions (e.g., positive versus negative) for each participant, the average PANAS Positive Affect High Activation score change over time remained non-significant. However, the Chi Square analysis of the difference between the Models 2 and 3 ($\chi^2\Delta$ = 4.77, p = 0.092). Although not statistically significant, Model 3 provided a better fit to the data compared to Model 2. This result indicated that, although PANAS Positive Affect High Activation slopes might be significantly changing over time for some of the sample participants, the sample's PANAS Negative Affect Total average slope change over time remained non-significant.

Model 5 (Table 20; random intercept and random slope where scores were allowed to vary across both time and participants) showed that participants in the high risk category demonstrated slopes over time that differed from other participants, and this difference was statistically significant ($b = 0.63$, $SE = 0.28$, $\chi^2 \Delta = 4.99$, $p < 0.05$). This result indicated that, amongst the high recidivism risk participants, the increase in PANAS Positive Affect High Activation scores demonstrated greater rise across time than amongst participants in the low and moderate recidivism risk categories, with this difference being statistically significant. The magnitude of this increase was such that, with every additional month after the start of their probation, the higher recidivism risk category participants reported approximately 2/3 (63%) of a point higher on the PANAS Positive Affect High Activation scale than the participants in the moderate and low risk categories over the same time period.

A graphical representation of the difference in PANAS Positive Affect High Activation slopes over time for high versus low-to-moderate recidivism risk participants is provided in Figure 5 below. As seen in Figure 5, and consistent with previous positive affect analyses, PANAS Positive Affect High Activation did not demonstrate a statistically significant change over time in the low-to-moderate recidivism risk group; however, a visible overall increase in PANAS Positive Affect High Activation over time was statistically significant in the high recidivism risk participant group.

Figure 5

Simple Slopes Derived from a Multilevel Model (Table 19, Model 5) Depicting PANAS Positive Affect High Activation across Time for High vs. Low-to-Moderate Recidivism Risk Category Participants



Cox regression survival analyses

The PANAS Positive Affect High Activation subscale was further examined using Cox Regression survival analyses (with time-varying predictors), which predicts recidivism outcome while also accounting for the timing when predictors were assessed and the timing of recidivism outcomes. This type of exploratory analysis of PANAS Positive Affect High Activation was considered important to determine if PANAS Positive Affect High Activation would emerge as significant dynamic predictor of recidivism for this sample of adults on probation. Additionally, the static variable of participants' recidivism risk category was added to Cox regression models to further explore whether PANAS Positive Affect High

Activation predicts recidivism after accounting for risk for recidivism, as assessed by validated risk of recidivism tools.

Table 21

Cox Regression Survival Analysis (With Time-Varying Predictors) Hazard Ratios From Models Using PANAS Positive Affect High Activation and Recidivism Risk Category to Predict Recidivism Outcomes

Variable	*B*(*SE*)	exp(*B*) [95%CI]	*z*	*p*-value
Model 1 (*N* = 554 assessments from 307 individuals; 50 recidivism events)				
PANAS Positive Affect: High Activation	-0.065 (0.022)	0.94 [0.89, 0.98]	-2.93	0.0035**
Model Fit				
Wald test / Concordance	8.54 (*df* = 1, *p* = 0.003) / 0.65			
Model 2 (*N* = 484 assessments from 260 individuals; 44 recidivism events)				
PANAS Positive Affect: High Activation	-0.065 (0.023)	0.94 [0.89, 0.98]	-2.76	0.0058**
Risk Score Category = Low (Reference = High)	-2.758 (0.633)	0.06 [0.02, 0.22]	-4.35	<0.001***
Risk Score Category = Moderate (Reference = High)	-1.105 (0.323)	0.33 [0.18, 0.63]	-3.42	0.00062***
Model Fit				
Wald test / Concordance	28.88 (*df* = 3, *p* < 0.001) / 0.73			
Model 3 (*N* = 484 assessments from 261 individuals; 44 recidivism events)				
PANAS Positive Affect: High Activation	-0.047 (0.030)	0.95 [0.89, 1.01]	-1.58	0.11
Risk Score Category = High	2.439 (1.112)	11.46 [1.29,101.34]	2.19	0.03*
PANAS Positive Affect: High Activation* Risk Score Category = High	-0.043 (0.048)	0.96 [0.87, 1.05]	-0.90	0.37
Model Fit				
Wald test / Concordance	30.65 (*df* = 3, *p* < 0.001) / 0.68			

*$p < .05$; **$p < .001$, ***$p < .0001$ (two-tailed)

Table 21 presents Cox regression models using PANAS Positive Affect High Activation and recidivism risk category to predict recidivism outcomes. Model 1 showed that PANAS Positive Affect High Activation was inversely and significantly related to recidivism outcomes (B = -0.065, SE = 0.022, p < 0.001). Exponentiating the coefficient to gain a hazard ratio (exp (B) = 0.94, 95% CI = 0.89, 0.98) revealed that for every 1 point increase in PANAS

Positive Affect High Activation scale, participants were 6% less likely to recidivate in the time period subsequent to that assessment.

In Model 2, risk of recidivism was added in a categorical way (with higher risk as a reference category) to the Cox regression model, with both low (B = -2.758, SE = 0.633; exp (B) = 0.06, 95% CI = 0.02, 0.22, $p < 0.0001$) and moderate risk categories (B = -1.105, SE = 0.323; exp (B) = 0.33, 95% CI = 0.18, 0.63, $p < 0.0001$) being inverse significant predictors of recidivism outcomes in the expected manner: participants in the low recidivism risk category scores were 94% less likely to recidivate compared to those in the high category risk, while participants in the moderate risk category scores were 67% less likely to recidivate compared to those in the high category risk. However, PANAS Positive Affect High Activation also remained a significant independent predictor in this model (B = - 0.065, SE = 0.022; exp (B) = 0.94, 95% CI = 0.89, 0.98, $p < 0.001$), demonstrating that PANAS Positive Affect High Activation is a significant predictor of recidivism outcomes even after controlling for the participants' recidivism risk category, such that for every 1 point increase in PANAS Positive Affect High Activation scale, participants were 6% less likely to recidivate in the time period subsequent to that assessment while accounting for recidivism risk scores.

In Model 3, we sought to explore whether the interaction between PANAS Positive Affect High Activation and the high recidivism risk category created a compounding effect, such that those with high risk of recidivism who also reported high PANAS Positive Affect High Activation would be at a significantly higher risk of recidivism. The Model 3 results demonstrated that the interaction between high risk and PANAS Positive Affect High Activation was not a significant predictor of recidivism outcomes.

Overall, the Cox regression results demonstrated that PANAS Positive Affect High Activation was a significant predictor of recidivism outcomes when modelled on its own in

Model 1 (Table 21), as well as remaining significant even after accounting for the predictive power of participants' recidivism risk category (Model 2), such that for every 1 point increase in PANAS Positive Affect High Activation scale, participants were 6% less likely to recidivate in the time period subsequent to that assessment. This result indicates that positive emotions with high behavioural activation (e.g., feeling enthusiastic, excited, proud, strong) remained significant predictors of recidivism outcomes even after accounting for participants' recidivism risk category.

PANAS Positive Affect – Low Activation

Multilevel modelling

The PANAS Positive Affect Low Activation subscale was examined using multilevel modelling (MLM) analyses, to explore if any potential change-over-time patterns exist for PANAS Positive Affect Low Activation scale for the study adult probation sample. This type of exploratory analysis was considered important to determine if and how positive affect low in behavioural activation (e.g., feeling calm, content, peaceful, relaxed) might fluctuate for adults on supervision over time. Additionally, multilevel modelling was further utilised to explore if individuals' age at start of supervision, their gender, or recidivism risk category status have any relationship with the degree of low behavioural activation positive affect change over time for this participant cohort.

Table 22 below outlines the exploratory MLM results for PANAS Positive Affect Low Activation scale. In Model 1, the intercept value displayed in Column 2 (b = 17.09, SE = 0.32) represents the average PANAS Positive Affect Low Activation score for the study participants across the entire sample (i.e., when individual scores across different participants and different time points were all taken into consideration). To place this average sample score into a context, the PANAS Positive Affect Low Activation scores can range from 5 to 25 (see Table 6; the scale has a total of 5 items rated on a Likert scale from 1-5).

Furthermore, Model 1 also shows the Intraclass Correlation Coefficient (ICC) value, a descriptive statistic which explains how much of the intercept score variance is due to the person, and how much of the intercept variance is due to external circumstances (such as different assessment times). In Model 1, the ICC score of 0.54 indicated that 54% of the total variance in PANAS Positive Affect Low Activation scores can be attributed to similarities in scores for the same participant across time, while 46% of total variance can be attributed to the differences in assessment scores over time within the same person.

Model 2 (Table 22, random intercept, fixed slope) was subsequently used to examine whether the sample average on the PANAS Positive Affect Low Activation scores would change significantly over time; this model was not significant, showing the sample, on average, did not demonstrate change in scores through time.

Furthermore, in Model 3 (Table 22, random intercept, random slope), where scores were allowed to change at different rates and in different directions (e.g., positive versus negative) for each participant, the average PANAS Positive Affect Low Activation score change over time remained non-significant. However, the Chi Square analysis of the difference between the Models 2 and 3 was statistically significant ($\chi^2 \Delta = 6.23$, $p < 0.05$); with Model 3 providing a statistically significantly better fit to the data compared to Model 2. This better model-to-data fit result indicated that PANAS Positive Affect Low Activation slopes might be significantly changing over time for some of the sample participants; however, the sample's PANAS Positive Affect Low Activation average slope change over time remained non-significant.

Table 22

Multilevel Model Unstandardized Coefficients Predicting PANAS Positive Affect Low Activation Across Multiple Assessments (Minimum of 2, Maximum of 4) and Examining Longitudinal Growth Across Time and Interaction Between Time and Age, and Interaction with Time and Gender Using Restricted Maximum Likelihood Estimation

Variable	Random Intercept	Random Intercept and Fixed Slope	Random Intercept and Random Slope				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Fixed Effects							
Mean Negative Affect Total							
Intercept	17.09 (0.32)	17.10 (0.33)	17.13 (0.33)	17.12 (0.33)	17.13 (0.33)	17.24 (0.37)	17.26 (0.38)
Age at Release	-	-	-	0.061 (0.027)	0.059 (0.027)	-	-
Gender (Female)	-	-	-	-	-	-0.48 (0.79)	-0.59 (0.80)
Linear Slope							
Time in Months	-	-0.017 (0.034)	0.028 (0.038)	0.0028 (0.039)	0.0024 (0.039)	0.0036 (0.0039)	-0.016 (0.044)
Age at Release	-	-	-	-	0.0022 (0.0032)	-	-
Gender (Female)	-	-	-	-	-	-	0.086 (0.092)
Random Effects							
Variance Components							
Level 1 (residual)	12.29	12.30	10.59	10.56	10.57	10.59	10.56
Level 2 (intercept)	14.58	14.62	15.26	14.89	14.89	15.30	15.34
Level 2 (time)	-	-	0.048	0.049	0.049	0.048	0.049
Model Fit							
AIC	2627.0	2658.8	2656.5	2653.6	2655.1	2658.2	2686.9
BIC	2669.3	2675.2	2681.2	2682.3	2687.9	2659.3	2692.1
ICC	ICC = 0.54	-	-	-	-	-	-
χ^2 Δ from prior model	-	χ^2 Δ = 0.24	χ^2 Δ = 6.23*	χ^2 Δ = 4.96*	χ^2 Δ = 0.48	χ^2 Δ = 0.36	χ^2 Δ = 0.88

Note. N = 450 assessments from 182 individuals

*p < .05; **p < .001, ***p < .0001 (two-tailed)

In Model 4 (Table 22; random intercepts and random slopes), participant age at start of probation was added to MLM in order to explore whether older versus younger participants reported higher or lower levels of PANAS Positive Affect Low Activation over time. Table 22 shows that the age estimate for Model 4 was statistically significant (b =

0.061, *SE* = 0.027, $\chi^2 \Delta = 4.96$, $p < .05$), indicating that older participants had on average reported significantly higher PANAS Positive Affect Low Activation scores than younger participants. However, although this result was statistically significant, it was also very slight, such that for every year of increased age, older participants were likely to report only 6% of a point higher PANAS Positive Affect Low Activation score. In other words, the age difference between younger and older participants would have to amount to a minimum of 17 years before an average increase of one point on the PANAS Positive Affect Low Activation score for older participants would be observed.

In Model 5, we explored if there was an association between participant age and the magnitude or direction of their slope across time, i.e., whether participants of different ages may generally show different degrees of change in PANAS Positive Affect Low Activation across time. However, in Model 5, the age estimate was not statistically significant and did not assist understanding how individuals' PANAS Positive Affect Low Activation scores change across time.

In Models 6 and 7 (Table 22; random intercepts and random slopes), participant gender (female) was added to the model to explore whether changes in PANAS Positive Affect Low Activation over time could be related to participant gender. Model 6 showed that, although female participants had on average scored half a point lower on the PANAS Positive Affect Low Activation scale, this decrease in average scores related to gender was not statistically significant, and therefore not meaningful with regards to any significant gender differences in PANAS Positive Affect Low Activation scores. Furthermore, examining whether average slopes tended to differ in female versus male groups in the sample, Model 7 was also not statistically significant. Overall, Models 6 and 7 (Table 22) demonstrated that participant gender is not a significant consideration in explaining the patterns of PANAS Positive Affect Low Activation change over time for the study sample.

The next variable of exploratory interest in relation to examining the change of PANAS Positive Affect Low Activation scores over time was the participants' risk of recidivism category. Notably, these models were run on a smaller sample due to a larger amount of missing information for the recidivism risk category, as compared to the participant age or gender information. As a result of a smaller sample, Models 1-3 were re-run in order to explore whether recidivism risk status was related to Positive Affect Low Activation slopes within this smaller sample. Subsequently in Models 4 and 5, the high recidivism risk category was added to the multilevel modelling. The results of these analyses are presented in Table 23 below:

Table 23

Multilevel Model Unstandardized Coefficients Predicting PANAS Positive Affect Low Activation Across Multiple Assessments (Minimum of 2, Maximum of 4) and Examining Longitudinal Growth Across Time and Interaction Between Time and Recidivism Risk Category Using Restricted Maximum Likelihood Estimation

Variable	Random Intercept	Random Intercept and Fixed Slope	Random Intercept and Random Slope		
	Model 1	Model 2	Model 3	Model 4	Model 5
Fixed Effects					
Mean Negative Affect Total					
Intercept	17.13 (0.34)	17.14 (0.34)	17.20 (0.34)	17.09 (0.36)	17.12 (0.36)
High Risk Status	-	-	-	1.14 (1.11)	1.67 (1.11)
Linear Slope					
Time in Months	-	-0.032 (0.038)	0.0044 (0.045)	0.0054 (0.045)	-0.028 (0.044)
High Risk Status	-	-	-	-	0.69 (0.22)
Random Effects					
Variance Components					
Level 1 (residual)	12.07	12.03	9.91	9.90	9.72
Level 2 (intercept)	13.52	13.65	14.09	14.26	14.25
Level 2 (time)	-	-	-	0.066	0.056
Model Fit					
AIC	2319.8	2321.0	2317.7	2318.7	2310.3
BIC	2331.7	2336.9	2341.6	2346.6	2342.1
ICC	ICC = 0.54	-	-	-	-
χ^2 Δ from prior model	-	χ^2 Δ = 0.72	χ^2 Δ = 7.28*	χ^2Δ =1.04	χ^2 Δ = 10.42**

Note. N = 395 assessments from 161 individuals

*p < .05; **p < .001, ***p < .0001 (two-tailed)

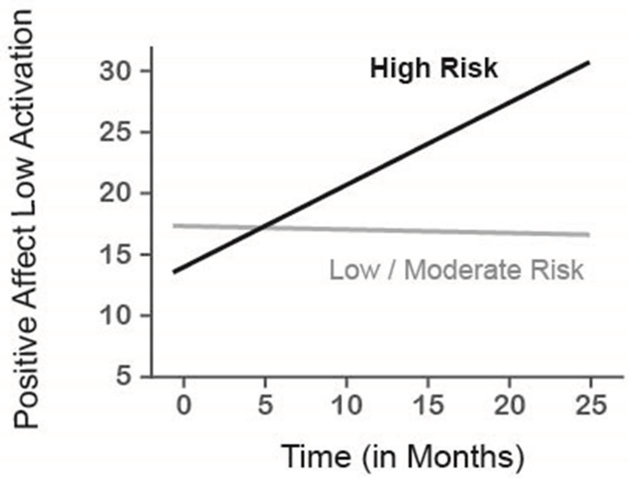
In Model 3 (Table 23, random intercept, random slope), where participants' scores were allowed to change at different rates and in different directions (e.g., positive versus negative) for each participant, the average PANAS Positive Affect Low Activation score change over time remained non-significant. However, the Chi Square analysis of the difference between the Models 2 and 3 was statistically significant ($\chi^2\Delta$ = 7.28, p < .05) with Model 3 providing a statistically significant better fit to the data compared to Model 2. This result indicated that, although PANAS Positive Affect Low Activation slopes might be significantly changing over time for some of the sample participants, the sample's PANAS Positive Affect Low Activation average slope change over time remained non-significant.

Model 5 (Table 23; random intercept and random slope where scores were allowed to vary across both time and participants) showed that participants in the high risk category demonstrated slopes over time that differed from other participants, and this difference was statistically significant (*b* = 0.69, *SE* = 0.22, $\chi^2 \Delta$ = 10.42, $p < 0.001$). This result indicated that, amongst the high recidivism risk participants, the growth in PANAS Positive Affect Low Activation scores demonstrated greater increases across time than amongst participants in the low and moderate recidivism risk categories, with this difference being statistically significant. The magnitude of this increase was such that, with every additional month after the start of their probation, the higher recidivism risk category participants were likely to report approximately 2/3 (69%) of a point higher on PANAS Positive Affect Low Activation scale than the participants in the moderate and low risk categories over the same time period.

A graphical representation of the difference in PANAS Positive Affect Low Activation slopes over time for high versus low-to-moderate recidivism risk participants is provided in Figure 6 below. As seen in Figure 6, and consistent with previous positive affect scales, PANAS Positive Affect Low Activation did not demonstrate a statistically significant change over time in the low-to-moderate recidivism risk group; however, a visible overall increase in PANAS Positive Affect Low Activation over time was statistically significant in the high recidivism risk participant group.

Figure 6

Simple Slopes Derived from a Multilevel Model (Table 22, Model 5) Depicting PANAS Positive Affect Low Activation across Time for High vs. Low-to-Moderate Recidivism Risk Category Participants



Low / Moderate Risk slope, p = 0.52; High Risk slope, p = 0.001

Cox regression survival analyses

The PANAS Positive Affect Low Activation subscale was further examined using Cox Regression survival analyses (with time-varying predictors), which predicts recidivism outcome while also accounting for the timing when predictors were assessed and the timing of recidivism outcomes. This type of exploratory analysis of PANAS Positive Affect Low Activation was considered important to determine if PANAS Positive Affect Low Activation would emerge as significant dynamic predictor of recidivism for this sample of adults on probation. Additionally, the static variable of participants' recidivism risk category was added to Cox regression models to further explore whether PANAS Positive Affect Low

Activation predicts recidivism after accounting for risk for recidivism, as assessed by validated risk of recidivism tools.

Table 24

Cox Regression Survival Analysis (With Time-Varying Predictors) Hazard Ratios From Models Using PANAS Positive Affect Low Activation and Recidivism Risk Category to Predict Recidivism Outcomes

Variable	*B*(*SE*)	exp(*B*) [95%CI]	*z*	*p*-value
Model 1 (*N* = 560 assessments from 309 individuals; 52 recidivism events)				
PANAS Positive Affect: Low Activation	-0.124 (0.028)	0.88 [0.84, 0.93]	- 4.37	<0.0001***
Model Fit				
Wald test / Concordance	19.1 (*df* = 1, *p* < 0.001) / 0.68			
Model 2 (*N* = 488 assessments from 262 individuals; 46 recidivism events)				
PANAS Positive Affect: Low Activation	-0.116 (0.031)	0.89 [0.84, 0.94]	- 3.81	0.00014***
Risk Score Category = Low (Reference = High)	-2.604 (0.631)	0.07 [0.02, 0.25]	- 4.13	<0.0001***
Risk Score Category = Moderate (Reference = High)	-1.017 (0.317)	0.37 [0.20, 0.69]	- 3.20	0.0013**
Model Fit				
Wald test / Concordance	34.11 (*df* = 3, *p* < 0.001) / 0.74			
Model 3 (*N* = 488 assessments from 262 individuals; 46 recidivism events)				
PANAS Positive Affect: Low Activation	-0.117 (0.037)	0.89 [0.83, 0.96]	- 3.17	0.0015**
Risk Score Category = High	1.472 (0.964)	4.36 [0.65, 28.88]	1.53	0.13
PANAS Positive Affect: Low Activation* Risk Score Category = High	-0.009 (0.063)	0.99 [0.88, 1.12]	- 0.14	0.89
Model Fit				
Wald test / Concordance	33.47 (*df* = 3, *p* < 0.001) / 0.70			

*p < .05; **p < .001, *** p < .0001 (two-tailed)

Table 24 presents Cox regression models using PANAS Positive Affect Low Activation and recidivism risk category to predict recidivism outcomes. Model 1 showed that PANAS Positive Affect Low Activation was inversely and significantly related to recidivism outcomes (B = -0.124, SE = 0.028, p < 0.0001). Exponentiating the coefficient to gain a hazard ratio (exp (B) = 0.88, 95% CI = 0.84, 0.93) revealed that for every 1 point increase in PANAS Positive Affect Low Activation scale, participants were 12% less likely to recidivate in the time period subsequent to that assessment.

In Model 2, risk of recidivism was added in a categorical way (with higher risk as a reference category) to the Cox regression model, with both low (B = -2.604, SE = 0.631; exp (B) = 0.07, 95% CI = 0.02, 0.25, $p < 0.0001$) and moderate risk categories (B = -1.017, SE = 0.317; exp (B) = 0.37, 95% CI = 0.20, 0.69, $p < 0.01$) being inverse significant predictors of recidivism outcomes in the expected manner: participants in the low recidivism risk category scores were 93% less likely to recidivate compared to those in the high category risk, while participants in the moderate risk category scores were 63% less likely to recidivate compared to those in the high category risk. However, PANAS Positive Affect Low Activation also remained a significant independent predictor in this model (B = -0.116, SE = 0.031; exp (B) = 0.89, 95% CI = 0.84, 0.94, $p < 0.001$), demonstrating that PANAS Positive Affect Low Activation is a significant predictor of recidivism outcomes even after controlling for the participants' recidivism risk category, such that for every 1 point increase in PANAS Positive Affect Low Activation scale, participants were 11% less likely to recidivate in the time period subsequent to that assessment while accounting for recidivism risk scores.

In Model 3, we sought to explore whether the interaction between PANAS Positive Affect Low Activation and the high recidivism risk category created a compounding effect, such that those with high risk of recidivism who also reported high PANAS Positive Affect Low Activation would be at a significantly higher risk of recidivism. The Model 3 results demonstrated that the interaction between high risk and PANAS Positive Affect Low Activation was not a significant predictor of recidivism outcomes.

Overall, the Cox regression results have demonstrated that PANAS Positive Affect Low Activation was a significant predictor of recidivism outcomes when modelled on its own in Model 1 (Table 24), as well as remaining significant even after accounting for the predictive power of participant's recidivism risk category (Model 2), such that for every 1 point increase in PANAS Positive Affect Low Activation scale, participants were 11% less likely to recidivate in the time period subsequent to that assessment. This result indicates that positive emotions with low behavioural activation (e.g., feeling calm, content, peaceful, relaxed) remained significant predictors of recidivism outcomes even after accounting for participants' recidivism risk category.

PANAS Positivity Ratio Total

Cox regression survival analyses

The PANAS Positivity Ratio was further included in the exploratory analyses and examined using Cox Regression survival analyses (with time-varying predictors). In general, positivity ratio refers to the overall proportion of positive versus negative emotions experienced by individuals across time. We sought to explore whether the positivity ratio, viewed as a form of an interaction where positive emotion must be more heavily weighted than negative emotion across the balance of positive and negative emotions over time for effective goal-directed behaviours to occur, would be related to recidivism among the study participants.

In the context of this study, an exploratory PANAS Positivity Ratio analysis was therefore considered relevant to determine if PANAS Positivity Ratio Total would potentially emerge as significant dynamic predictor of recidivism for this sample of adults on probation. To achieve this, several variations of PANAS Positivity Ratio calculations (ordered from mathematically more simple to more complex) were utilised in different Cox regression survival analyses models to explore whether PANAS Positivity Ratio Total holds any predictive power for recidivism outcomes, over and above of what was already accounted for by its independent components (e.g., PANAS Negative Affect Total and PANAS Positive Affect Total), or their non-ratio interaction term alone. Table 25 below summarises the Cox regression survival analysis models examining different potential forms of the PANAS Positivity Ratio (e.g., PANAS Positivity Ratio calculated as a simple ratio, 1 / PANAS Positivity Ratio, Log PANAS Positive and Negative Affect Total), as modelled while advancing in complexity to always prioritise controlling for individual positivity ratio components when simultaneously testing the positivity ratio, to predict recidivism outcomes.

The positivity ratio calculations approach we used in the current study has also been used in previous studies. The following three journal articles can be used as reference points for the positivity ratio calculations we employed in this study: Certo, Busenbark, Kalm & LePine (2020); Kronmal, (1993) and Emerson (2016).(Certo, Busenbark, Kalm, & LePine, 2020; Emerson, 2014; Kronmal, 1993)

Table 25

Cox Regression Survival Analysis (With Time-Varying Predictors) Hazard Ratios From Models Using PANAS Positivity Ratio and Positive – Negative Affect Interactions to Predict Recidivism Outcomes

Variable	*B*(*SE*)	exp(*B*) [95%CI]	*z*	*p*-value
Model 1 (*N* = 560 assessments from 309 individuals; 52 recidivism events)				
PANAS Negative Affect	0.0059 (0.0096)	1.01 [0.99, 1.02]	0.62	0.53
PANAS Positive Affect	-0.045 (0.014)	0.96 [0.93, 0.98]	-3.11	0.0019**
Model Fit				
Wald test / Concordance	14.6 (*df* = 2, *p*< 0.001) / 0.66			
Model 2 (*N* = 560 assessments from 309 individuals; 52 recidivism events)				
PANAS Negative Affect	0.010 (0.024)	1.01 [0.96, 1.06]	0.41	0.68
PANAS Positive Affect	-0.040 (0.029)	0.96 [0.91, 1.02]	-1.35	0.18
PANAS Negative Affect*PANAS Positive Affect	-0.00014 (0.00080)	0.9999 [0.9983, 1.001]	-0.18	0.86
Model Fit				
Wald test / Concordance	14.9 (*df* = 3, *p* = 0.002) / 0.66			
Model 3 (*N* = 560 assessments from 309 individuals; 52 recidivism events)				
PANAS Negative Affect**	0.0040 (0.015)	1.00 [0.97, 1.03]	0.27	0.79
PANAS Positive Affect**	-0.041 (0.024)	0.96 [0.92, 1.01]	-1.75	0.08
Positivity Ratio Total	-0.105 (0.055)	0.99 [0.30, 2.65]	-0.19	0.85
Model Fit				
Wald test / Concordance	14.3 (*df* = 3, *p* = 0.002)/ 0.66			
Model 4 (*N* = 560 assessments from 309 individuals; 52 recidivism events)				
PANAS Negative Affect	0.038 (0.057)	1.04 [0.93, 1.16]	0.66	0.50
PANAS Positive Affect	0.053 (0.15)	1.05 [0.79, 1.41]	0.35	0.72
1/ PANAS Negative Affect	27.88 (79.64)	1.28e+12 [2.1e-56, 7.84e+79]	0.35	0.73
Positivity Ratio Total	-1.41 (2.39)	0.24 [0.0022, 26.74]	-0.59	0.56
PANAS Negative Affect*PANAS Positive Affect	-0.0015 (0.0021)	0.998 [0.994, 1.003]	-1.70	0.48
Model Fit				
Wald test / Concordance	15.38 (*df* = 5, *p* = 0.009)/ 0.67			
Model 5 (*N* = 560 assessments from 309 individuals; 52 recidivism events)				
PANAS Negative Affect	0.018 (0.038)	1.01 [0.94, 1.09]	0.47	0.64
Log PANAS Negative Affect	0.28 (3.66)	0.96 [0.001, 1733.19]	0.08	0.94
Model Fit				

Wald test / Concordance	5.93 (*df* = 2, *p* = 0.05) / 0.58			
Model 6 (*N* = 560 assessments from 309 individuals; 52 recidivism events)				
PANAS Positive Affect	-0.091 (0.066)	1.91 [0.80, 1.04]	-1.36	0.17
Log PANAS Positive Affect	3.18 (4.98)	24.01 [0.0014, 416 000]	0.64	0.52
Model Fit				
Wald test / Concordance	13.27 (df = 2, p = 0.001) / 0.66			
Model 7 (*N* = 560 assessments from 309 individuals; 52 recidivism events)				
PANAS Negative Affect High Activation	0.01 (0.034)	1.01 [0.94, 1.08]	0.33	0.74
PANAS Positive Affect Low Activation	-0.108 (0.05)	0.89 [0.81, 1.99]	-2.12	0.03*
Positivity Ratio Mixed: Positive Affect Low Activation / Negative Affect High Activation	-0.075 (0.452)	0.93 [0.38, 2.25]	-0.16	0.86
Model Fit				
Wald test / Concordance	19.44 (*df* = 3, *p* = 0.002) / 0.68			

*$p < .05$; **$p < .001$, ***$p < .0001$ (two-tailed)

** PANAS Positive and Negative Affect were not centred in the analyses

We first sought to explore whether PANAS Positive Affect Total is significantly related to recidivism even after simultaneously accounting for PANAS Negative Affect Total. The Model 1 showed that PANAS Positive Affect Total was inversely and significantly related to recidivism outcomes, regardless of the existing level of PANAS Negative Affect Total (B = -0.045, SE = 0.014, $p < 0.001$). Exponentiating the coefficient to gain a hazard ratio (exp (B) = 0.96, 95% CI = 0.93, 0.98) revealed the size of this effect was such that for every 1 point increase in PANAS Positive Affect Total, participants were 4% less likely to recidivate in the time period subsequent to that assessment, after controlling for degree of negative affect. As such, PANAS Positive Affect Total remained significantly related to recidivism even after controlling for the PANAS Negative Affect Total, i.e., independently of PANAS Negative Affect Total presence and/or degree. In other words, regardless of the existing level of PANAS Negative Affect Total (which could range from zero to very high), the PANAS Positive Affect Total still remained significantly related to recidivism.

In Model 2, we further sought to explore whether the interaction between PANAS Positive Affect Total and PANAS Negative Affect Total created a compounding effect, such that the effect of PANAS Positive Affect Total on recidivism might be linked in some way to the level of Negative PANAS Negative Affect Total. The Model 3 results demonstrated that the interaction between PANAS Negative Affect Total and PANAS Positive Affect Total was not a significant predictor of recidivism outcomes.

In Model 3, the PANAS Positivity Ratio Total was first introduced, as calculated in its simplest ratio way (i.e., PANAS Positive Affect Total / PANAS Negative Affect Total). In this model, we sought to explore whether the PANAS Positivity Ratio as an independent variable holds any predictive power towards recidivism outcomes, after accounting for its singular components, i.e., PANAS Positive Affect Total and PANAS Negative Affect Total. With regards to the differences between Model 2 and Model 3, the introduction of PANAS Positivity Ratio in Model 3 is recognizing that a positivity ratio is a different type of an interaction effect between PANAS Positive and Negative Affect Total, which takes into the account previous research indicating that an occurrence of negative affect can have a stronger effect than the occurrence of positive affect, such that a higher ratio of positive to negative affect may be needed to counteract the direct effects of negative affect on person's wellbeing or behaviour. However, Model 3 results demonstrated that PANAS Positivity Ratio Total, when calculated as a simple ratio, did not emerge as a significant predictor of recidivism outcomes in this sample. It is also important to note that Model 3 represented the arguably most lenient test of the PANAS Positivity Ratio Total, where individual components of the ratio components had remained in their linear (non-transformed) forms, leading to the highest likelihood of finding an effect of the PANAS Positivity Ratio in the Cox regression survival analysis, if there was one.

However, despite not finding a statistically significant predictive effect of PANAS

Positivity Ratio (when accounting for its linear components) in Model 3, we sought to further explore whether mathematically more complex ways of calculating the PANAS Positivity Ratio would lead to the same outcome in this sample. As a result, in Model 4 we added a variable calculated as 1 / PANAS Negative Affect (which, mathematically, is one of two components of the PANAS Positivity Ratio when multiplied with PANAS Positive Affect). Including both components in the model alongside the simple positivity ratio effectively controls for the ratio's component parts as a stricter test of the importance of the positivity ratio as a predictor. Model 4 also controlled for the PANAS Negative and Positive Affect Total interaction term, to provide an even stricter test of whether the positivity ratio has independent predictive power beyond its sub-components. However, Model 4 results demonstrated that PANAS Positivity Ratio remained a non-significant predictor of recidivism outcomes.

In Models 5 and 6, the logarithmic variable transformations of PANAS Positive Affect Total and PANAS Negative Affect Total, respectively, were introduced into Cox regression models. The logarithmic transformation accounts for the possibility that the initial experiences of any type of affect may influence behaviour more than the compounding effects of further subsequent affective experiences. As such, a person who was experiencing positive emotions prior to one negative emotion emerging into their experience may find this more impactful than the subsequent impact of additional negative emotions within the same time period. In other words, the logarithmic versions of PANAS Positive Affect Total and the PANAS Negative Affect Total were calculated to account for previous positivity ratio research indicating potential exponential scaling of the magnitude of influence that initial affective experiences have over the subsequent affect experiences, as they accumulate over time. In both models, we first controlled for the linear (original) version of the variables, to test if those simpler variable versions better predicted recidivism outcomes than their logarithmic versions. Both Models 5 and 6 models demonstrated that the logarithmic versions of PANAS Positive and Negative Affect Total did not emerge as significant predictors of recidivism outcomes, leading to the conclusion that accentuating the value of initial affect experiences through a logarithmic variable was not contributing beyond the simple versions of the variables.

Finally, in Model 7, we sought to explore whether a mixed version of the PANAS Positivity Ratio held any predictive power towards recidivism outcomes, after accounting for its singular components, i.e., PANAS Positive Affect Low Activation and PANAS Negative Affect High Activation. This exploratory analysis was conducted on the basis that both components emerged as significant predictors of recidivism outcomes in prior analyses, even after controlling for recidivism risk category. However, Model 7 results demonstrated that PANAS Positivity Ratio Mixed (i.e., PANAS Positive Affect Low Activation / PANAS Negative Affect High Activation), when calculated as a simple ratio, did not emerge as a significant predictor of recidivism outcomes in this sample. It is also important to note that Model 7 represented an arguably lenient test of the PANAS Positivity Ratio Mixed, where individual components of the ratio components had remained in their linear (non-transformed) forms, leading to the highest likelihood of finding an effect of the PANAS Positivity Ratio Mixed in the Cox regression survival analysis, if there was one.

Overall, the PANAS Positivity Ratio exploratory analyses showed that PANAS Positivity Ratio, calculated in several ways, does not hold any predictive power towards recidivism outcomes for this sample of study participants.

Chapter Five: Discussion

Overview

The present study was an exploratory analysis of whether any significant relationships exist between the self-reported dynamic experiences of positive and negative affect among adults on probation and recidivism outcomes, while attending to established static recidivism risk factors such as participants' age, gender, and recidivism risk category as simultaneous predictors or moderators of change. A three-wave, prospective research design involved a total of 352 adults on probation recruited from two different US correctional partnering agencies: a Texas state probation agency (280 participants), and an Oklahoma federal probation agency (72 participants). The analyses explored several static recidivism risk factors (i.e., participants' age, gender and risk of recidivism category) measured once, with dynamic affect variables (Positive Affect Negative Affect Scale (PANAS) subscales) measured over 650 separate assessment occasions intended as up to 3 assessment points per participant. The overall aim of the study was to explore the dynamic variables' ability to predict recidivism outcomes, and if any significant change over time existed for dynamic variables and if change may have been moderated by the three static risk variables. The two main statistical approaches used to achieve these goals were Cox regression survival analyses and multilevel modelling.

When analysing emotions, it is important to keep in mind multidimensionality across different affective states. The concept of affective multidimensionality originally stems from Russell's (1980) general emotion classification, where emotions were classified according to the dimensions of high arousal versus no arousal, and pleasure versus displeasure (Russell, 1980). As previously discussed, the notion that emotions are multi-faceted subsequently led to the development of The Circumplex Model of Emotions (Plutchik & Conte, 1997; Russell, 1997), a well-regarded affective model which suggests that emotions are best conceptualised along two bipolar dimensions: 1) high arousal / activation (e.g., active, excited) versus low arousal / activation (e.g., inactive, bored); and 2) pleasure (e.g., content, happy) versus displeasure (e.g., sad, angry). The Positive Affect Negative Affect Scale (PANAS), which was used in this study, was originally developed and adapted as a way of quantifying these two affective dimensions as outlined in the The Circumplex Model of Emotions.

One primary aim of the current study was to pursue Cox regression analyses of the PANAS subscales across its two valence dimensions (i.e., positive versus negative affect), and two behavioural activation dimensions (i.e., low versus high activation), with regards to each of the six subscales' dynamic ability to predict recidivism outcomes, in our sample of adults on probation.

Prediction of Recidivism

The Valence Dimension and Recidivism

Positive Affect and Recidivism

The predictive ability of the two valence-based PANAS subscales, i.e., overall positive affect (as assessed by PANAS Positive Affect Total) and overall negative affect (as assessed by PANAS Negative Affect Total) were examined with regards to their ability to predict recidivism outcomes. As outlined in Chapter 2, the potential influence of emotions on offending behaviour has been a peripheral topic of academic research within the criminology field, with any affect-related correctional research predominantly focused on exploring the influence of strong negative emotions on re-offending. As a result, anger was commonly found to have an activating effect on aggressive violent behaviour across different types of forensic settings, and especially when measured in its state rather than trait form (Craig, 1982; Daffern et al., 2005; Doyle & Dolan, 2006a, 2006b; McNiel et al., 2003; Novaco, 2011; Skeem et al., 2006; Zamble & Quinsey, 2001). In contrast, the existing research into the potential influence of positive affect on offending or re-offending behaviour has been even scarcer, and mostly confined to the relatively recent qualitative-based desistance-focused research (Farrall et al., 2014; Lebel et al., 2008). For example, maintaining desistance efforts in adults with offending histories was predominately linked with feeling positive rather than negative, with individuals who previously offended reporting feelings of pride at having desisted, as well as satisfaction with their lives and feelings of pleasure derived from prosocial roles such as parenthood, especially once stable desistance over time has been achieved (Farrall, Hunter, Sharpe, & Calverley, 2014).

A particularly relevant study in relation to the current research was completed by Brown et al (2009), who conducted a similarly designed three-wave, prospective study of static and dynamic recidivism prediction in a sample of Canadian adults on probation. As a brief reminder, Brown et al. (2009) included the repeated measures of positive and negative affect using the PANAS scale in their study, with the first assessment time occurring before the pre-correctional release of their participants, followed by two evenly spaced assessment times during their community probation. Brown et al.'s (2009) results showed that positive affect at Time 1 was inversely related to recidivism outcomes for their sample of adults on probation. Also, the dynamic positive affect measured over three time points across 3-5 months remained relatively stable, and positive affect was not a significant predictor of recidivism outcomes after controlling for other predictors, including negative affect. However, in the current sample of adults on probation who were followed-up for a period of 12-18 months, the overall self-reported dynamic positive affect notably emerged as a significant and inverse predictor of recidivism outcomes after controlling for static risk scores. Moreover, this finding remained significant even after accounting for both the presence and/or levels of participants' self-reported dynamic negative affect. The effect size of this result was such that for every one point increase on the PANAS Positive Affect Total scale (signifying increased self-reported frequency of total positive affect), the study participants were 5% less likely to recidivate in the time period subsequent to that assessment. Theoretically, this effect size indicates that approximately half of a standard deviation (5 points) difference in the PANAS Positive Affect Total scale from 41 points to 46 points (with the PANAS Positive Affect Total scale range of 12-60) would be related to a difference in sample recidivism by 25%, i.e., amounting to 10 fewer recidivism events in the current sample. In other words, a 5 point overall increase in the self-reported frequency of experiencing positive affect could theoretically be related to 44 instead of 54 recidivism events for this study sample, over the data collection period of 12-18 months.

To place this effect size into context, if an additional 5% recidivism reduction effect was somehow achieved in reality by paying closer attention to positive emotions of adults on probation, it would not be considered negligible given the modest effect sizes of 10-15% reduction in recidivism rates currently achieved among adults who offended after participating in evidence-based forensic psychological intervention. For example, a recent meta-analysis of adult recidivism treatment effectiveness was conducted by Gannon, Olver, Mallion and James (2019) for over 70 correctional studies with more than 55,000 adults who offended, with results indicating that recidivism treatment (both offense-specific and non-offense specific) resulted in recidivism rates of 13.4% for individuals receiving psychological treatment, as compared to 19.4% recidivism rates for the untreated individuals over an average follow up of 66.1 months (Gannon, Olver, Mallion, & James, 2019). Similarly, amongst populations of adults who offended violently, two comprehensive meta-analyses were conducted including only higher quality correctional studies, with results indicating that psychological treatments for adults with violent offences were effective in reducing recidivism by 8-10% for the treated individuals. Together, these meta-analytic findings highlight that recidivism treatment effectiveness is currently modest as indicated by effect sizes, with there being both a need for improvement in efficacy, and room to improve treatment effectiveness for adults with offending histories (Jolliffe & Farrington, 2007; Papalia, Spivak, Daffern, & Ogloff, 2019)

The current study finding regarding the significant predictive power of dynamic positive affect towards recidivism is somewhat inconsistent compared to the study reported by Brown et al. (2009), who detected significant predictive ability of dynamic positive affect towards recidivism outcomes when using positive affect as a sole predictor, but not when simultaneously controlling for risk scores or negative affect. In other words, when Brown et al. (2009) were accounting for results from all three of their consecutive assessment points of adults on probation which spanned up to five months, total PANAS overall positive affect did not emerge as a significant dynamic predictor of recidivism (i.e., scores did not change nor predicted recidivism after accounting for other predictors), while the opposite was found in the current study which spanned up to 18 months participation. However, because Brown et al (2009) found Time 1 PANAS total positive affect inversely predicted recidivism, this indicates that, in the Brown et al (2009) study results, PANAS positive affect held significant predictive ability towards recidivism outcomes from a static, rather than dynamic point of view (Brown et al., 2009).

When considering the potential reasons behind the differences in dynamic positive affect results between the two studies, several key study designs variations would be important to consider. Firstly, Brown et al.'s (2009) research design differed from the current study such that their assessment timings were regimented and evenly spaced over time, as opposed to the relatively irregular assessment timings achieved in the current study. For example, Brown et al.'s (2009) first wave of data collection (Time 1) occurred inside the Canadian correctional institution prior to participants' release, while the second and third waves of data collection occurred in the community, very close to participants' one and three month post-release dates (with a two week interviewing window allowed of seven days before and after the actual target dates). In contrast, all three data collection waves in the current study occurred at inconsistent time frames following participants starting their community probation. Although it was originally planned for the current study assessment times to be aligned with the start of probation, 3- and 6-month probation date mark, in practice this was unfortunately not consistently achieved, resulting in relatively unpredictable assessment time intervals across 18 months of probation. For this reason, the current study design did not allow for the direct testing of Time 1 assessment scores towards prediction of recidivism using logistic regression, as in Brown et al.'s (2009) study. As such, we were unable to directly explore whether Brown et al.'s (2009) Time 1 positive affect result would be replicated.

The second relevant difference between the two studies were the differing lengths of probation follow-up in each study, with the overall five month data collection ending after three months of community probation in Brown et al.'s (2009) study. In contrast, the current data collection spanned across 12-18 months of community probation per participant. As such, the current study had the advantage of accounting for significantly longer adult probation time-frame, which allowed for increased generalisation regarding the dynamic predictors' change patterns over time in the community.

Thirdly, it is possible that the participants' overall risk profile was substantially different between Brown et al.'s (2009) study and the current study, such that the current study sample involved a substantially lower recidivism risk participant cohort. Unfortunately, due to variations in the risk recidivism assessment tools used in Brown et al.'s (2009) study versus the current study, we were unable to directly compare recidivism risk either through the direct assessment scores, or via risk categories. However, a higher percentage of Brown et al.'s (2009) sample had offence histories inclusive of violent crimes (e.g., violent assaults), as opposed to the majority of the current study participants entering community probation due to non-violent crimes such as driving under influence or substance possession. Moreover, Brown et al.'s (2009) participants all had a history of incarceration and were released from correctional facilities before entering community supervision, whilst the majority of the current study sample was not incarcerated before starting their community probation. It is perhaps also relevant to mention the larger-scale differences between legal systems in Canada and the United States, with the former country likely being more stringent around convicting only adults with more serious offences (e.g., drug possession may generally be treated more harshly by the United States justice system than the Canadian justice system). When taken together, these details lend support to the possibility that the current study sample collected in the United States was characterised by an overall lower recidivism risk profile than Brown et al.'s (2009) sample.

Despite the discrepancies between the Brown et al (2009) and current study results in relation to the predictive ability of dynamic positive affect towards recidivism, the overall findings from both studies jointly imply that positive affect - a largely overlooked category of emotions with regards to both correctional research and practice - could be an important factor for helping predict recidivism outcomes for adults on community probation. The significant and inverse relationship that was found between the overall dynamic positive affect and recidivism outcomes in the current study over 12-18 months of community probation additionally appears to be a statistically significant novel finding that requires further research consideration and follow-up.

Moreover, the current study findings extended Brown et al.'s (2009) research by indicating that the predictive ability of positive affect towards recidivism outcomes could be applicable over and above the presence and/or levels of negative affect, as well as over and above what can be accounted for by the participants' recidivism risk categories. Yet, due to the overall paucity of existing knowledge related to links between positive affect and adult recidivism, the exact parameters of the relationship between the two remain to be further validated and explored. Additional research is needed and recommended in this area before firmer conclusions about the predictive ability of dynamic positive affect towards recidivism can be more reliably drawn.

Negative Affect and Recidivism

In the current study, overall negative affect (as assessed by the PANAS Negative Affect Total) was also examined with regards to its predictive ability towards recidivism outcomes. Our results demonstrated that total dynamic negative affect was a significant direct predictor of recidivism for the current sample of adult participants on probation. This particular result was also in line with the previous dynamic negative affect PANAS results reported by Brown et al (2009). However, the current study also extended the findings of Brown et al (2009) by modelling the overall negative affect whilst simultaneously controlling for the participants' static recidivism risk category. Interestingly, once the participants' recidivism risk category had also been accounted for, the overall PANAS negative affect became a non-significant predictor of recidivism. In other words, although overall negative affect was a significant dynamic predictor of recidivism when modelled on its own (in line with previous research results), further exploratory analyses indicated that its predictive power was adequately accounted for by participants' static recidivism risk category.

In turn, this implies that the information captured within standard risk of recidivism frameworks (based on known risk factors and criminogenic needs within the RNR model) seems to efficiently capture the predictive power of overall dynamic negative affect towards recidivism. This novel finding appears plausible, given that most recidivism risk assessment tools contain at least one assessment item related to the individual's level of negative emotionality, e.g., proneness to anger. Notably, these items on risk tools are rated by staff such as supervision officers or correctional clinicians, likely based on interview or behavioural indicators, whereas this study used self-reported negative emotions. However, it should be further noted that the standard risk of recidivism tools used in this study (Federal Post Conviction Risk Assessment (PCRA) and Texas Risk Assessment System (TRAS)) did not contain any specific risk assessment items targeting assessment of individuals' negative affect. This further implies there is a high likelihood that other common recidivism risk domains captured by PCRA and TRAS (e.g., criminal attitudes and behaviours, cognitions, violence items, substance use, social support, etc.) share enough variance with negative affectivity to effectively account for it, even without the inclusion of any specific affect-related risk assessment items. Overall, this particular finding suggests that a functional overlap exists in everyday practice between the overall negative affect levels (including self-reported negative affect) and the non-affect related recidivism risk domains, with regards to predicting recidivism outcomes. If validated in the future, this finding would indicate there is a lesser need to track ongoing changes in individuals' overall levels of negative affect as time on probation continues, in relation to improving prediction of recidivism outcomes, as standard recidivism risk category adequately captures this domain, albeit indirectly. However, a notable exception to this overall finding which emerged during further exploratory analyses is applicable to the highly activating negative affect states only (i.e., feeling uptight, angry, ashamed, stressed, nervous, guilty, and irritable). This exception is further discussed in the following section.

The Behavioural Activation Dimension and Recidivism

As mentioned previously, emotions can be best conceptualised through a multi-dimensional lens. In relation to the Circumplex Model of Emotions (Plutchik & Conte, 1997), the second dimension of exploratory interest in this study was the behavioural activation dimension (high versus low activation affect), which was examined across both positive and negative affective states. Highly activating affect, regardless of its valence, is thought to increase the likelihood of behaviours occurring, and was therefore considered of interest to explore in relation to predicting reoffending outcomes. In the following sections, we outline the current study results regarding the behavioural activation dimension for both positive and negative affect, with some unexpected results emerging related to their predictive contribution towards recidivism outcomes.

As a reminder, the items from the total PANAS scale were further subdivided to more specifically examine the seven highly activating positive emotions (i.e., feeling interested, alert, excited, active, enthusiastic, proud and strong), while the low activating positive affect included the remaining five PANAS positive emotions (i.e., feeling calm, at ease, content, peaceful, relaxed). Conversely, highly activating negative affect items included seven PANAS negative emotions (i.e., feeling uptight, angry, ashamed, stressed, nervous, guilty, and irritable), while low activating negative affect included the remaining 11 PANAS negative emotions considered to be low in behavioural activation (i.e., feeling hopeless, numb, quiet, depressed, inactive, sleepy, miserable, bored, sad, unhappy, tired).

Low Activation Positive Affect and Recidivism

The current study results demonstrated that both high and low behavioural activation positive affect were found to be statistically significant and inverse dynamic predictors of recidivism outcomes. Moreover, aside from being independently significant, both subscales also remained significant inverse dynamic predictors of recidivism outcomes even after accounting for participants' static recidivism risk categories. These results supporting either activation dimension as predictors also mirrors the previously discussed significant and inverse predictive ability of the overall positive affect towards recidivism outcomes, which remained significant even after controlling for participants' negative affect levels, as well as their recidivism risk category. Taken together, the current study findings are supportive of the overall importance of positive affect as a significant inverse and dynamic predictor of recidivism for adults on probation, inclusive of both activation levels.

Next, the specific effect sizes for each positive affect behavioural activation subscale with relation to their separate predictive power towards recidivism were considered of interest. The current study results have showed that for every one point increase on the PANAS Positive Affect High Activation scale, signifying higher self-reported frequency, the study participants were 6% less likely to recidivate in the time period subsequent to that assessment. This effect size was nearly identical to the effect size found for the overall PANAS positive affect, which suggested a 5% decrease in likelihood of recidivism in the subsequent assessment time period for every single point on PANAS Positive Affect Total scale increase. Further, this indicates that approximately one standard deviation (five points) difference in the PANAS Positive Affect High Activation scale - from a current sample average of 24 points to a sample average of 29 points (PANAS Positive Affect High Activation scale range of 7-35) - would be related to a difference in an overall sample reoffending by 30%, i.e., approximately 12 fewer recidivism events. In other words, a five point average sample difference in the self-reported frequency of experiencing high activation positive affect could theoretically be related to 42 instead of 54 recidivism events for this study sample, over the average community probation period of 12-18 months.

We further examined the effect size for the subscale measure of low activation positive affect (i.e., feeling calm, at ease, content, peaceful, relaxed), where a somewhat unexpected result emerged. In contrast to the already significant 5% and 6% reduction in recidivism events for every single point increase in positive affect total and high activation scales respectively, the low activation positive affect results indicated that for one point increase on the PANAS Positive Affect Low Activation scale, study participants were 12% less likely to recidivate in the time period subsequent to that assessment. In other words, the effect size for low activation positive affect (i.e., feeling calm, at ease, content, peaceful, relaxed) was, surprisingly, double the effect size found in both the overall positive affect and the high activation positive affect. Practically, this twice-the-effect-size indicated that an approximately one standard deviation (five points) difference in the Positive Affect Low Activation scale from a study sample average of approximately 17 points to a sample average of 22 points (with PANAS Positive Affect Low Activation scale range of 5-25) could be related to a difference in sample reoffending of 60%, i.e., amounting to an approximately 23 fewer recidivism events. In other words, a five point average sample difference in the self-reported frequency of experiencing low activation positive affect could theoretically be related to 31 instead of 54 recidivism events for this study sample, over the community probation period of 12-18 months. Importantly, this suggests the experience of positive affect with low activation may be more strongly related to desistance from crime and avoidance of recidivism compared to positive affect with high activation, to the degree that low activating positive emotions are twice as important than high activating positive emotions. In practice, this finding would suggest that probation officers with some people on their caseloads reporting lower average frequencies of low activation dynamic positive affect would need to pay closer attention to these probationer cohorts due to needing further personal stability toward achieving desistance from crime, compared to the adult probationers reporting stable or higher average frequencies of low activating positive emotions over time.

Taken together, these novel findings indicate that total positive affect is a potentially important predictor of recidivism outcomes for adults on probation. This is despite the fact that positive affect has not yet been adequately considered in criminology research more broadly, nor accounted for within the standardised recidivism risk assessment tools more specifically. Importantly, the current study finding of low activation positive affect (i.e., feeling calm, at ease, content, peaceful, relaxed) having twice-the-effect size with regards to its recidivism predicting ability, is considered particularly interesting as it suggests that the low activation dimension of positive affect could be particularly noteworthy to separately consider in any future research with regards to positive affect and recidivism outcomes.

In practice, the current study results also imply that probation officers would need to be better supported to assess and track positive affect frequency experienced by adults on probation, in order to maximise their chances of identifying probationers whose risk of recidivism may be heightening with lower self-reported positive affect frequencies. Paying attention to affective changes appears to be particularly salient for the low activation positive affect, which has not been highlighted nor distinguished in this way in previous research. Although significant, the overall findings regarding positive affect offered by the current research would also need to be validated by subsequent research before any firmer conclusions regarding positive affect and recidivism outcomes may be drawn.

High Activation Negative Affect and Recidivism

We further explored the behavioural activation dimension of negative affect and its predictive ability related to recidivism outcomes. Unsurprisingly, highly activating negative affect (i.e., feeling uptight, angry, ashamed, stressed, nervous, guilty, and irritable) emerged as a significant dynamic predictor of recidivism outcomes for this study sample of adults on probation. What was somewhat unexpected was that highly activating negative affect also remained a significant predictor even after controlling for the participants' recidivism risk category. This finding was contrary to findings using total scores and low activating negative affect scores, with both non-significant predictors of recidivism outcomes when also accounting for participants' recidivism risk category. This additional predictive power of highly activating negative affect, over and above participants' recidivism risk category, further indicates that highly activating negative affect could be an important recidivism predictor that is not yet adequately accounted for by the existing and commonly used recidivism risk assessment tools.

Further analysis of the effect sizes for the high activation negative affect revealed that, for every one point increase on the PANAS Negative Affect High Activation, signifying higher self-reported frequency, the adult study participants were 6% more likely to recidivate in the time period subsequent to that assessment. This effect size suggests that, theoretically, an approximately one standard deviation (five points) difference in PANAS Negative Affect High Activation scale - from a study sample average of 13 to 18 points (with PANAS Negative Affect High Activation scale range of 7-35) - would be related to a difference in sample reoffending by 30%, i.e., amounting to approximately 12 additional recidivism events. In other words, a five point average sample difference in the self-reported frequency of high activation negative affect could theoretically be related to 66 instead of 54 recidivism events for this study sample, over the average community probation period of 12-18 months. In practice, this would also suggest that the probation officers with probationers who are reporting higher average frequencies of highly activating negative affect over time would need to pay closer attention to these cohorts due to a potentially heightened risk of recidivism, as opposed to adult probationers reporting stable or lower frequencies of highly activating negative emotions over time.

The current study findings regarding highly activating dynamic negative affect emerging as a particularly significant contributor towards predicting recidivism may be unsurprising considering that re-offending is a behaviour that needs to be activated. Considering prior findings, the contrast in results highlights and raises questions about whether desistance from crime should be conceptualised as similarly activating (i.e., individuals using personal agency to choose desistance-relevant behaviours), or better conceptualised as a process of settling down or simply just opting out of crime (i.e., feeling satisfied with a life that excludes crime rather than explicitly choosing to work toward dis-engaging from being criminal). Yet, reoffending behaviour is theoretically and plausibly linked with the negative affect subtypes that are higher on the behavioural activation dimension. However, the more unexpected outcome of the current study is that, while standard risk of recidivism assessment tools seemed to adequately account for the predictive power of low activation subtypes and total negative affect towards recidivism, this result did not extend to high activation negative affect. This further indicates that more research and practice attention is needed with regards to specifically accounting for highly activating negative affect for adults on probation. In other words, best practice regarding negative affect monitoring may not be to track adults' overall negative affect patterns, rather, it may be to specifically track only the highly activating negative affect (e.g., feeling uptight, angry, ashamed, stressed, nervous, guilty, and irritable), in order to improve current ability to predict dynamic recidivism risk. Generally, this also suggests that probation officers may require training on how to track the highly activating negative affect states experienced by adults on probation, in order to maximise their chances of identifying those whose risk of recidivism may be rising. Still, although significant, these current study results would also need to be validated by subsequent studies, before any firmer conclusions regarding highly activating negative affect and recidivism outcomes may be drawn.

Dynamic Patterns of Positive and Negative Affect Over Time

Multilevel modelling analyses were employed to explore if any significant dynamic change patterns of positive or negative affect emerged over time in the current study. We sought to explore whether any dynamic affect changes might have been moderated by known static recidivism risk factors, such as participant age at start of the probation, gender, or recidivism risk category.

Positive Affect and Stability Over Time

Results did not suggest significant variability across time among positive affect scores for the current study sample, on average. Further, results did not indicate different degrees of change across time for different individuals, suggesting participants largely followed the sample's average trend. In other words, overall positive affect emerged as being a relatively stable variable, which was also in line with Brown et al.'s (2009) results related to dynamic positive affect. Additionally, the current study findings indicated affective stability was equally applicable across both high and low activation dimensions of positive affect. Generally, the overall pattern of positive affect stability over time and between individuals was not initially anticipated as positive affect was first conceptualised as a dynamic variable that was likely to show a natural pattern of fluctuation over time, in both Brown et al.'s (2009) and the current study.

The potential reasons behind the temporal stability of positive affect may have their origins in two concepts previously outlined as part of the broader research body on affect and affect-related cognitions, i.e., negativity bias, and the happiness set-point. As previously discussed, the negativity bias refers to the well-established human propensity towards higher automatic attention toward incoming negative information (as opposed to the neutral or positive information), with negative information also being more utilised and integrated in any subsequent thinking, learning and communication (Baumeister et al., 2001; Bebbington et al., 2017; Morewedge, 2009; Rozin & Royzman, 2001). This effect has been aptly summarised by Roy Baumeister and his colleagues as "bad is stronger than good" (Baumeister et al., 2001). The stability of dynamic positive affect over time could be considered in the context of this well-known negativity bias phenomenon, which suggests that daily positive events may be weaker in capturing and holding our attention, and thus may fail to induce any statistically significant patterns of fluctuations in positive affect across our daily lives, thus contributing to its relative stability. Conversely, the negativity bias research also provides theoretical support for the significant patterns of negative affect fluctuations that were found in average dynamic negative affect over time in the current study of adults on probation.

Another potential explanation for the stability of positive affect levels over time could be that an optimal ‘happiness set-point’ exists for each individual. The existence of such a set-point means that even highly positive life-changing events, such as winning the lottery jackpot, would lead to (at best) a temporary increase in positive affect that would be followed by an eventual return to a baseline happiness set-point (Brickman et al., 1978). This is also consistent with the general adaptation level theory (Helson, 1964), that current happiness levels are likely to be relative to individualised previous peak happiness experiences, current mundane daily experiences, or peer group experiences. Two underlying processes hypothesised to support maintenance of a hedonic adaptation and happiness set-point were contrast and automatic habituation (as discussed in Chapter 2).

The current study findings regarding the overall stability of positive affect over time are consistent with the automatic habituation effect and the happiness set-point. As previously discussed, it is possible that the automatic negativity bias plays a role in maintaining the happiness set-point by automatically redirecting and maintaining focus towards perceived negative events (even after very positive events), thus promptly levelling out any positive affect spikes that otherwise could be more prominent in our emotional lives. The negativity bias could therefore be indirectly contributing to the overall dynamic stability of positive affect across time.

In summary, the temporal stability of dynamic positive affect PANAS scales has now been demonstrated across two separate repeated measures studies with multiple assessment points, suggesting that: (i) dynamic positive affect shows a pattern of stability over time which appears to extend up to 18 months for adults on probation; (ii) the overall stability of average positive affect in adults on probation should be considered in future correctional research. This is particularly relevant because stability of positive affect appears to be in direct contrast to the significant patterns of changeability in negative affect over time, which was demonstrated across both the current study and Brown et al.'s (2009) study.

Negative Affect and Change Over Time

Multilevel modelling was again used for exploratory analyses of the negative affect subscales, to examine whether any significant change existed in negative affect over time. In direct contrast to the previously discussed temporal stability of positive affect over time, negative affect among study participants significantly differed such that negative affect scores changed across time using all three versions of PANAS Negative Affect, i.e., total, low activation and high activation. Further, results indicated that negative affect fluctuated significantly over time in different ways for different individuals with regards to both its direction of change (positive or negative) and its slope of change (slower or faster), for all three negative affect subscales. The significant dynamic changes in PANAS negative affect over time for different individuals in this study were also in line with the dynamic negative affect results from previous research (Brown et al., 2009). However, the statistically significant degree of individual-level change found in this study was initially masked by the finding that there was non-significant change in the sample scores, on average, for negative affect over time.

As previously mentioned, the dynamic variability of negative affect across individuals over time could perhaps also be understood in the context of a larger body of research related to the attentional 'negativity bias'. It is plausible to suggest that this human propensity to automatically place greater emphasis on perceived self-threatening, negative events (even if these may be relatively small daily annoyances, such as being cut-off by another driver in traffic) would subsequently result in accompanying spikes of negative affect at various time-points across our daily lives, when such individualised events occur. These negative affect fluctuations would also differ significantly across different individuals with regards to their timing, direction and the slope of change until the perceived negative events are resolved, at which point higher negative affect levels return towards more neutral mood.

Participant Age and Positive / Negative Affect Change

Multilevel modelling analyses were further employed to explore whether participants' age at the start of their probation would have a significant relationship with the degree of dynamic changes in positive and negative affect over time. Across all three positive affect subscales, no significant effect emerged to suggest the degree of positive affect over time was moderated by participant age. Further, older participants in our study reported the same average positive affect scores as the younger participants. Although cross-sectional, this finding therefore suggests that positive affect remains stable across participants of different ages, as well as longitudinally within each individual (during the 18-month study period).

The stability of overall positive affect across age in the current study compliments the much wider body of research regarding the longitudinal stability of positive affect from early to late adulthood across genders, countries and cultures (Carstensen et al., 2000; Carstensen et al., 2011; Charles et al., 2001; Gross et al., 1997). Given that the majority of our current study participants were adults on probation in their mid-30s to early-40s, the current results lend support to the overall body of research suggesting stability of positive affect in the general populations of the same age span. One potential explanation for the relative stability of positive affect over the lifespan could be the previously discussed mechanism of hedonic adaptation, and the existence of an optimal happiness set-point to which individuals keep defaulting even after experiencing significant ups and downs of life. An alternative explanation may be that affective experiences become more stable as individuals mature, due to the increasingly efficient self-regulatory processes which develop with age (Charles & Pasupathi, 2003; Röcke, Li, & Smith, 2009). However, no firm conclusions can be drawn regarding the positive affect stability over individual lifespan at this time due to the prevalence of cross-sectional studies only in this research field, as longitudinal lifespan research remains difficult to conduct due to its length and the complexities of collecting information related to physical, emotional, and social functioning across many decades (Carstensen et al., 2011).

Notably, however, several previous studies that have assessed positive affect in older adults have reported only a slight decrease in positive affect occurring for adults in their 60s to mid-80s (Carstensen et al., 2011; Charles et al., 2001). It has been suggested that such decline in positive affect, often referred to as the terminal drop, may be related to an increased awareness of a decreased distance from dying at older age, or to the declining cognitive ability (Gerstorf et al., 2008). However, the current study results did not reflect this effect due to majority of study participants being well below age 60.

We also sought to explore whether participants' age at the start of their probation might have a significant moderating relationship with dynamic changes in the negative affect scales across time. The current study results showed that, across all three PANAS negative affect subscales (total, high and low activation), older participants had, on average, reported either statistically significant (for total and low activation negative affect), or nearly statistically significant (for the high activation negative affect) lower scores than the younger participants. Despite statistical significance, these results were also relatively slight in their magnitude; for example, the age difference between the younger and the older participants would have to amount to a minimum of 5 years for the total negative affect, 20 years for the highly activating negative affect, and 8 years for the low activation negative affect, before an average decrease of only one point on each respective scale score would be observed in the older participants. Regardless of the relatively low magnitude, the currently observed trend is in line with the much wider body of research identifying a slow decrease in negative affect from early to late adulthood in general populations of men and women across different countries and cultures (Charles et al., 2001), with older adults experiencing negative affect less frequently than younger adults (Basevitz et al., 2008; Carstensen et al., 2000; Mroczek & Kolarz, 1998; Phillips et al., 2008).

As previously detailed, theories in the current literature suggest several potential reasons may underlie a decrease in negative affect with ageing, including: the socio-emotional selectivity theory which postulates that older adults tend to prioritize emotionally fulfilling goals due to a growing awareness of a reduced life-span over time (Carstensen, 2006); that older age is related to cognitively more benign appraisals of negative stimuli than younger age (Charles & Carstensen, 2010); that older adults have more leisure time (outside of work and school) to engage in positive experiences of their choice which reduce their negative affect experiences (Ginn & Fast, 2006); or that the older adults emotionally benefit from an age –related reduction in the frequency of daily stressors, such as reduced work hours (Charles et al., 2010). Older adults could also simply have a decreased reactivity to daily stressors due to improved emotion regulation skills acquired over their life experience (Birditt & Fingerman, 2003; Birditt et al., 2005). Although the longitudinal research related to decreases in negative affect over individuals' lifespan remains ongoing, the current study results suggest that adults on probation may also experience a reduction in their overall negative affect as they age, in line with what has been reported in the general population research. However, the age-related results from the current study were cross-sectional as the longitudinal component did not extend further than 12-18 months to examine change related to aging.

Participant Gender and Positive / Negative Affect Change

Next, gender-related differences in dynamic patterns of average positive and negative affect were explored using multilevel modelling analyses for all versions of the PANAS subscales. The current study results demonstrated no statistically significant differences in the degree of change in positive and negative affect over time by gender group.

However, adult females on probation who participated in the current study scored, on average, one point lower on the PANAS Positive Affect Total and two points higher on the PANAS Negative Affect Total, compared to adult males who participated in the study. Although this was a statistically non-significant difference between genders, when these average affect scores are considered together, they might suggest that females who participated in this study could have been feeling worse overall than the males in the study. Yet, as is often the case in correctional research, the relatively low proportion of females in our study sample (25%) was a limiting factor for further exploring any gender differences in more detail. In general, due to the overall paucity of studies exploring dynamic affect in correctional research, there are no previous studies known to the author at this time that would suggest that the non-significant finding of the current study is either typical or atypical for adults on probation. It therefore remains possible that, in a larger sample with a more balanced gender profile, significant gender-related differences regarding averages of or change in positive and negative affect over time could emerge. Furthermore, the possibility of significant affect-related gender differences was considered conceivable based on the background of previous dynamic affect-based research in the general population, where studies have consistently reported that women tend to experience more intense emotions than men (Birditt & Fingerman, 2003; Fischer & Manstead, 2000; Fujita, Diener, & Sandvik, 1991), and that women tend to experience negative emotions for a longer duration of time than men (Birditt & Fingerman, 2003; Fischer & Manstead, 2000). These previous research findings in the general populations could also help contextualise the higher average negative affect noted for the adult females on probation in the current study, despite this difference being statistically non-significant compared to males. It is recommended that future research is needed before any firmer conclusions can be drawn.

Participant Recidivism Risk Category and Positive / Negative Affect Change

We further sought to explore if a moderating relationship existed between participants' static recidivism risk category (as determined by correctional staff's risk ratings on standardised recidivism risk assessment tools) with the degree of positive and negative affect change over time.

The current study results demonstrated that, after separating participants in the high risk category from participants in the low or medium risk categories, there was a statistically significant and distinct increase over time in dynamic positive affect across all three positive affect subscales (total, high activation and low activation) for the high recidivism risk category participant group. The magnitude of the high recidivism risk group increase in positive affect over time was such that, with every additional month after the start of their probation, the higher recidivism risk participants were likely to report approximately 1.3 point higher on the positive affect total scale; 2/3 of a point higher on the high activation positive affect scale, and 2/3 of a point higher on the low activation positive affect scale, compared to the participants in the low and moderate recidivism risk categories.

This result was surprising, as it substantially deviates from the previously established finding indicating general stability of positive affect over time in this participant sample, on average, and specifically amongst low-to-moderate risk category participants. Moreover, the high recidivism risk cohort's dynamic increase in positive affect also deviates from the much wider body of research that points towards lifespan stability of positive affect for general populations of both men and women across different countries and cultures (Carstensen et al., 2000; Carstensen et al., 2011; Charles et al., 2001; Gross et al., 1997). This current study result thus indicates a possibility that the high recidivism risk adults on probation could also represent a theoretically important population group, who significantly differ from both the average correctional and non-correctional populations, by displaying a pattern of increasing positive affect over a relatively short period of time (up to 18 months). Given that there is significant research interest in high recidivism risk participants, it would be important for future research to consider attempting to replicate this novel finding, as well as to further explore it, if validated.

In parallel with increasing positive affect, the current study results also demonstrated that across all three PANAS subscales measuring dynamic negative affect (total, high activation and low activation), negative affect decreased at a greater rate in the high recidivism risk participant group than in the low or moderate recidivism risk groups. This difference was nearing statistical significance for all three negative affect subscales. The magnitude of this negative affect decrease was such that, with every additional month after the start of their probation, higher recidivism risk category participants were likely to report approximately 1 point lower on the negative affect total scale; 1/3 of a point lower on the negative affect high activation scale, and 2/3 of a point lower on the negative affect low activation scale compared to the participants in the low and moderate recidivism risk categories. Despite these results only nearing statistical significance, it is intriguing that the same trend emerged across all negative affect subscales. Together, study results appear to indicate that high recidivism risk individuals, beyond unexpectedly self-reporting steady rises in overall levels of positive affect while on probation, also reported near-significant faster reductions in their overall negative affect compared to low-to-moderate recidivism risk individuals.

Firstly, these reductions in negative affect over time were consistent with the general pattern of gradual, albeit slight, reduction of negative affect over time found in the low-to-moderate risk category participants. Furthermore, this overall trend is consistent with a larger body of research that has consistently reported a very gradual, but steady decrease in experiences of negative affect occurring from early to late adulthood among general populations of men and women across different countries and cultures (Charles et al., 2001). Previous research has consistently shown that older adults report experiencing negative affect less frequently than younger adults (Basevitz et al., 2008; Carstensen et al., 2000; Mroczek & Kolarz, 1998; Phillips et al., 2008).

However, the more unexpected aspect of the current study findings is that, within our participant sample, the rate of reduction in dynamic negative affect occurred at a faster rate within the high recidivism risk group, compared to the low-to-moderate recidivism risk groups. Secondly, when both positive and negative affective trends for the high recidivism category group were considered together, this indicates that the high recidivism risk study participants felt increasingly better (i.e., progressively less negative and more positive as their time on probation continued) compared to their low-to-moderate risk counterparts. As well as unexpected, it is also unclear why this combined effect of lower negative and higher positive affect may be occurring specifically in the high recidivism risk cohort. Perhaps several potential explanations could be cautiously hypothesised.

Firstly, it is possible that the lower retention rates of high recidivism category participants over time introduced a possible selection bias that contributed to the effect of changes in both positive and negative affect over time. In other words, the decrease in negative and the increase in positive affect over time for the high recidivism risk group could have been a consequence of high-risk cases with an overall negative emotional profile (i.e high negative and low positive affect scores) being more likely to drop out from the study over time, leaving only high risk cases with less negative emotions and more positive affect present.

It could also be that the two potentially independent effects are reflections of a singular effect, such that reductions in negative affect are simply a direct mirror image of the corresponding increase in positive affect. Although this link may be somewhat plausible, the most current view is that positive and negative affect are best conceptualised as existing independently of each other, as they can be felt concurrently (e.g., during states of emotional ambivalence), rather than being viewed as polar opposite ends of the same emotional continuum. Additionally, the positivity ratio results from the current study (discussed further below in this Chapter) also showed that the current total positive affect remained a significant dynamic predictor of recidivism even when accounting for participants' dynamic negative affect, suggesting there was an independent effect of each emotional valence on participants' recidivism outcomes.

Perhaps contributing to their overall rise in their positive affect, as high-risk individuals' time on probation extends without repeated re-offending (or return to court or prison), the high recidivism risk group may feel increasingly more positive about their prospects of staying crime-free in the long-term. Furthermore, the increase in positive affect on probation may also be a reflection of high-risk individuals receiving incremental rewards (e.g., probation officers rewarding their good behaviour by reducing mandated check-ins frequency, with more and more freedom being granted for their ongoing compliance), thus boosting participants' positive mood. Another potential explanation could be linked with the effects of abstinence from substance use, such that the high recidivism risk cohort feels increasingly positive on probation because they are beginning to reap both the physical and emotional benefits of successfully maintaining sobriety over time. Conversely, a less hopeful but perhaps similarly plausible hypothesis might be that high-risk participants are likely to revert to substance use whilst on community probation, and that their resumed substance use contributes to lower ratings of negative affect and higher ratings of positive affect over time. Notably, adults on probation in the United States are subjected to randomised drug testing as part of their community probation, a practice which has the potential to act as strong deterrent for ongoing substance use whilst on probation. Nevertheless, the overall rigorousness of the randomised drug testing for adults on probation in the United States is also not considered to be of a high enough frequency to guarantee that all illicit substance use would be readily detected during the community probation period, thus not excluding a possibility of ongoing (undetected) substance use.

Another potential explanation for increasing dynamic positive affect in the high recidivism risk group could also be linked to participants' personality traits, which may also play a role in determining individuals' propensity towards experiencing higher positive affect. For example, previous research in the field of emotion and personality has shown that one of the most robust findings is a positive relationship between extraversion and positive affect, with a negative relationship between neuroticism and positive affect (Costa, McCrae, & Arenberg, 1980; Diener & Lucas, 1999; Lucas & Fujita, 2000; Mroczek & Kolarz, 1998; Williams, 1990). According to the classical PEN (Psychoticism, Extraversion, Neuroticism) Model of Personality (Eysenck, 1977), individuals who are higher in extraversion (E) could also be characterized as more sociable, verbally expressive, and driven by the search of adventures and new experiences, while those lower in extraversion have a lesser need for environmental stimulation to maintain optimal arousal levels. While individuals with high neuroticism (N) are likely to suffer from more anxiety, depression, and emotional instability, as well as having higher reactivity to unfavourable stimuli, those who are lower in neuroticism are thought to have more robust and stable nervous systems which do not overreact to the stimuli of the environment. Additionally, individuals who score high on psychoticism (P) scale have initially been described as having a 'tough-minded nature', which is accompanied by a higher tendency towards aggressive, cold, ego-centric, and impulsive behaviour (Eysenck, 1977).

Relevant to explaining the potential links between higher risk of anti-social behaviours and individuals' personality traits, Eysenck originally suggested that high E individuals are under-aroused and therefore require higher levels of stimulation to learn, making them less conditionable than low E individuals (Eysenck, 1964; Eysenck & Eysenck, 1970). Eysenck further postulated that the conditioning of a conscience is an integral part to developing an ability to refrain from anti-social behaviour and that difficulty in developing a conscience is what makes individuals capable of being antisocial (Eysenck, 1996a). Eysenck also suggested that individuals who offend would likely have higher levels of both E and N, indicating that the interplay between having a central nervous system that is hard to condition but is also high in unstable emotional drives towards impulsive behaviour, would lead to even more difficulties in refraining from anti-social behaviours (Eysenck, 1996a). As research in this field had progressed over time, Eysenck and his colleagues transferred the impulsivity domain from E to the new psychoticism (P) personality dimension, continuing the theoretical predictions concerning the connection between high E, high N and offending behaviour, while adding that high P individuals would be especially prone to becoming antisocial (Eysenck, 1996b).

The overall empirical research regarding connections between personality traits and anti-social behaviour has this far demonstrated some mixed (and therefore relatively inconclusive) results. For example, Eysenck and Gudjonsson (1989) reviewed the available research on the PEN model and anti-social behaviour at the time. They reported that higher E appeared to be linked with individuals offending at younger ages, while higher N appeared to be linked with offending at older ages, with higher P still being most strongly related to offending behaviour overall (Eysenck & Gudjonsson, 1989). While some research reviews indicated a support for the link between extraversion and anti-social behaviour (Feldman, 1993), other studies have found support for the relationship between psychoticism and delinquency, but not for extraversion or neuroticism and delinquency (Furnham & Thompson, 1991). In a more recent meta-analysis of 59 studies on various structural models of personality and anti-social behaviour, Miller and Lyman (2001) found that personality dimensions reflecting low conscientiousness and low agreeableness were most consistently related to offending behaviour (Miller & Lynam, 2001). Although it is still generally agreed that the concept of personality traits has much to offer to the field of criminology, the current body of research in this field remains somewhat inconclusive about potential links due to inconsistent results.

Yet, there is relatively stronger evidence of links between personality traits and positive affect. For example, Charles, Reynolds & Gatz (2001) found that adults who scored higher on N also had lower initial positive affect scores and were more likely to decrease in positive affect scores over time. In contrast, individuals who scored higher on E were more likely to have higher initial levels of positive affect, and were able to maintain higher levels of positive affect compared to individuals lower in extraversion (Charles et al., 2001). Thus, if there is systematic overlap between high E (low receptivity to conditioning, higher need for sensation, and low conscientiousness), higher positive affect, and higher risk for recidivism, it is plausible that higher risk individuals also reported higher affect through extraversion (as defined by Eysenck).

McCrae and Costa (1991) further suggested two broad explanations that may help explain a link between positive affect and extraversion. The 'temperament model' theory suggests there is a direct link between the trait and the affective outcome, with some personality models going as far to suggest that positive affect is the core of the extraversion trait (Lucas, Diener, Grob, Suh, & Liang, 2000; Watson & Clark, 1997; Watson & Tellegen, 1985). In contrast, the 'instrumental model' theory suggests that personality traits indirectly influence the affective outcomes through preferential choices of situations or other intervening processes. In this vein, some researchers have proposed a 'sociability model' of extraversion, suggesting that active social contact is the key factor behind the increase in positive affect for most people (both introverts and extraverts). However, because extraverts tend to be significantly more sociable than introverts, extraverts are more likely to engage in more frequent social activity than do introverts, and thus experience higher levels of positive affect (Pavot, Diener, & Fujita, 1990). However, subsequent research had shown that the amount of social activity could not completely account for the link between extraversion and positive affect, as most of the effect appeared to be a direct effect (Lucas, Le, & Dyrenforth, 2008).

An alternative model of extraversion, named the 'reward sensitivity model', postulates that individuals who have an underlying positive incentive motivational system, i.e., who are more motivated by reward stimuli than have sensitivity to punishment via negative stimuli, are both more extraverted ones and more likely to experience higher levels of positive affect. In the support of this model, an in-depth analysis by Lucas et al. (2000) of a diverse international sample of participants from 39 nations who completed the same extraversion scales found that only facets reflecting reward sensitivity loaded on a higher order extraversion factor; this factor correlated strongly with positive affect (Lucas et al., 2000). They concluded that sociability, although an important part of extraversion, may be a by-product of an increased reward sensitivity which was hypothesised to be a more central aspect of extraversion than sociability (Lucas et al., 2000).

Based on the overall body of research regarding the links between personality traits, positive affect and anti-social behaviour, it could be hypothesised that the high recidivism risk individuals in this study may, in some way, have significantly different personality profiles when compared to low-to-moderate recidivism risk cohort, e.g., they could be higher in extraversion than their low-to-moderate risk counterparts, more reward-focused, more sociable, and less aware or attuned to formal and informal sanctions. The underlying personality differences could be a contributing factor in explaining the gradual rise of high recidivism risk participants' positive affect over time on probation. However, it is impossible to determine using the current data whether this is a plausible explanation, without further research including assessment of both personality traits and dynamic positive affect in the high recidivism risk adult cohorts. Unfortunately, this study did not include measures of sociability, extraversion, etc.

Finally, it is possible that a combination of the previously discussed hypotheses (in addition to others that have not been considered here) could together help explain why high recidivism risk individuals in this study appear to experience increasingly positive affect as their time on probation continues. Although, putting aside the possible reasons underlying this study finding, it could also be speculated whether this increase of positive affect among the high recidivism risk cohort could also become their 'Achilles heel' in terms of their recidivism outcomes. In other words, feeling increasingly positive over time on community probation might lead to the development of 'fake confidence', which would see high recidivism risk individuals perhaps becoming overly confident in their progress, and thus increasingly complacent about attending to their risk factors. As a part of this process, the high recidivism risk individuals may begin to think: "I feel great, everything is going so well, why not just do (substance use / contact the anti-social peers / etc.) this one time only…". Having increased confidence to safely engage in a risky behaviour due to feeling better, a form of cognitive distortion known as emotional reasoning, may in turn trigger a cascade of behaviours leading to a potential relapse in substance use and/or re-offending. In other words, it may be possible there is a relationship between increasing positive affect and corresponding recidivism risk, such that feeling progressively more positive over time (and perhaps losing sight of being cautious) could be a relevant factor underpinning recidivism outcomes for the high-risk participant group. Indeed, this hypothesis may have support from the finding that the low-moderate recidivism risk participants showed marked stability in dynamic positive and negative affect over time on probation, with perhaps very slight tendency towards decline across both types of affect. It could also be important to note that this observed tendency toward overall stability of self-reported affect in the low-to-moderate recidivism risk group, a stability which is absent in the high recidivism risk group, is an important element of low risk individuals' ability to ultimately maintain desistance from crime. Dynamic emotional stability reported over time may also reflect low-risk individuals' ability to moderate their own emotions more effectively than the high recidivism risk cohort. Self-regulation may also be related to potentially different underlying personality characteristics. In other words, whilst an increased amount of self-reported positive emotions might be important component in helping to reduce individuals' risk of reoffending through increasing pride and satisfaction at maintaining a crime-free lifestlye, it might alternately be that improved ability to maintain stability of affect over time, both positive and negative emotions alike, is what truly makes a crucial difference toward reducing individuals' overall recidivism risk.

Despite that only theoretical speculations can feasibly be offered at this stage with regards to possible reasons that underlie the high recidivism risk group's affective trends found in the current study, these results still suggest that high recidivism risk participants may be an important group that is, in some way, meaningfully different from both the average correctional and general populations in relation to having distinct patterns of positive and negative affect change over time. Future research in this area is therefore needed to further validate and explore this finding in more depth.

The Positivity Ratio and Recidivism

Both quantitative and qualitative research examining positive and negative affective states indicate that they are unlikely to exist in a complete vacuum from each other, as well as indicating that these states tend to increasingly be experienced concurrently as individuals get older (Carstensen et al., 2011; Maruna, 2001). Moreover, previous correctional research into emotions and desistance has also suggested that the transition pathway from offending to stable desistance is likely to be laced with states of 'emotional ambivalence', e.g., desisters will simultaneously experience negatively valanced feeling of regret for past involvement in crime, as well as positively valanced feeling of pride regarding new positive self-identification as a 'family man' (Lebel et al., 2008; Maruna, 2001). In the context of emotional ambivalence being both present and potentially relevant for desistance maintenance over time, the interactions between positive and negative affect in the form of a positivity ratio were considered relevant to explore in this study regarding any predictive ability towards recidivism outcomes.

The positivity ratio is a term used to describe a specific type of positive to negative affect interaction, signifying the overall ratio of positive versus negative affective experiences as they are experienced in individuals' lives across time. The overall PANAS Positivity Ratio was therefore calculated in the current study to explore whether this form of affect interaction, representative of the individuals' 'balance of emotional valence' over time, might influence prediction of recidivism outcomes for the study participants.

The exploratory analyses regarding positivity ratio in this study were also considered in the wider context of the previously discussed negativity bias research, which has repeatedly demonstrated that "bad is stronger than good", and that the experiences of positive emotions would need to significantly outnumber the experiences of negative emotions to overcome the adverse impact of negative emotions on wellbeing (Baumeister et al., 2001). A pioneer in the field of positivity ratio research, Gottman (1993) found that a positivity ratio on 5:1 for verbal communication and 4.7:1 for observed emotions was noted amongst the lasting marriages that both partners found satisfying. Conversely, for couples who were heading towards separation, a mean positivity ratio of 0.9:1 was found for verbal communication and 0.7:1 for observed emotion (Gottman, 1993). Importantly, Gottman's (1993) findings indicated that it may be possible to predict behavioural outcomes (such as a divorce) through paying a closer attention to the dynamic ratios of positive and negative emotions across time, and their associated interpersonal verbal interactions.

In the context of the current study, an exploratory PANAS positivity ratio analysis was considered to determine if PANAS Positivity Ratio Total could potentially emerge as significant dynamic predictor of recidivism in our sample of adults on probation. However, the current study results showed that PANAS Positivity Ratio Total did not emerge as a significant predictor of recidivism outcomes, after controlling for the individual positive and negative affect components. This non-significant positivity ratio result was consistently replicated across the multiple exploratory analyses involving different calculations of the positivity ratio, with increasingly stringent mathematical criteria applied. Although there was poor likelihood of observing a statistically significant prediction effect in the more complex models after demonstrating no effect using the least complex model, it was important to demonstrate various options for rigorously exploring a potential ratio effect. Future researchers who may find a prediction effect using a simpler model are advised to further consider if they have adequately controlled for subcomponents of the ratio that may instead be driving the prediction effect.

Prior to using different approaches for calculating the positivity ratio (Certo et al., 2020; Emerson, 2014; Kronmal, 1993), we initially tested for the predictive power of total positive affect whilst also accounting for the total negative affect. The results revealed that total positive affect remained a significant inverse independent predictor of recidivism outcomes in the current study sample, regardless of the overall negative affect presence and /or levels. The effect size of this result was such that for every 1 point increase in PANAS Positive Affect Total, participants were 4% less likely to recidivate in the time period subsequent to that assessment. In other words, regardless of the existing level of total negative affect, the total overall positive affect remained significantly and inversely related to recidivism in our study sample.

As a second step, a simple interaction term involving overall positive and negative affect was included to explore whether the overall positive affect was compounded in any way by the overall negative affect in relation to its predictive ability towards recidivism for adults on probation. This interaction term was not a significant predictor of recidivism outcomes, after first controlling for each of its components.

Subsequently, the PANAS overall positivity ratio was introduced in its mathematically simplest linear ratio form; however, the linear positivity ratio did not emerge as a significant predictor of recidivism outcomes when also controlling for its individual components. The potential predictive contribution of positivity ratio was then further explored through several mathematically different methods of calculating the positivity ratio. For example, logarithmic transformations of overall positive and negative affect variables were introduced in order to account for the primacy effect, a well-known cognitive processing bias that is often described as the tendency for the initial affective experiences to hold more influence in memory and attitude formation than the effects of any subsequent affective experiences, given that individuals generally fail to process later stimuli information as carefully as early information (Crano, 1977; Gilbert, 1991; Hendrick & Costantini, 1970). However, despite introducing the logarithmic transformation of dynamic positive and negative affect to account for the cognitive processing primacy effect, the overall PANAS logarithmic version of the positivity ratio remained a non-significant predictor of recidivism outcomes in this sample. Moreover, the same non-significant prediction result occurred when exploring other positivity ratio calculations using additional PANAS behavioural activation dimensions, from more simple to more complex ways.

In summary, results of the current study suggested that the basic components contained within the PANAS positivity ratio, i.e., the PANAS positive and negative affect scales, are significant dynamic predictors of recidivism outcomes for the current participant cohort, while conceptualising these components within a positivity ratio failed to add further benefit for predicting recidivism. This finding may indicate that an overall simpler model, inclusive of the affective components only, is a more meaningful and useful way to understand likelihood of recidivism outcomes for adults on probation as opposed to using a ratio approach. It might also be of interest to further explore, replicate, and re-validate these results in future research with adults on probation.

Study Limitations

Despite encouraging insights gained from the current study, the conclusions which can be drawn upon from the results are restricted by several study limitations.

Firstly, the study attrition rates were not ideal, with 52.8% of participants returning for the second session, and only 30.9% returning for a third assessment session. Despite no significant differences between the study completers and drop-outs at assessment Times 2 or 3 with regards to participant gender, language and index offence, significantly fewer high recidivism risk participants (as compared to the low risk participants) returned for the second assessment session. As for potential reasons for this discrepancy, it is likely that low recidivism risk participants are more socially engaged and thus willing to continue volunteering their time to participate in the study, compared to high recidivism risk participants, who may be less likely to volunteer their time repeatedly. Additionally, it is feasible that the higher risk participants were unavailable for follow-up due to higher re-offending rates. Unfortunately, the lower retention rates of high recidivism category participants over time contributed to lower study power to detect dynamic effects within this cohort of interest. It also introduced a possible selection bias in the interpretation of changes in emotions over time, so that decreases in negative and increase in positive affect over time could have been a consequence of high-risk cases with an overall negative emotional profile (i.e high negative and low positive affect scores) being more likely to drop out.

Secondly, missing data is one of the most pervasive problems for any data analysis, and even more so for repeated measures designs (Tabachnick & Fidell, 2007). Unsurprisingly, a proportion of missing items was present in the current study, ranging from 0.8% to 13.7% for the static variables such as participant age, gender and recidivism risk categories, then extending up to 18.3% for the dynamic positive affect variables and up to 23.4% for the dynamic negative affect variables. While the percentage of missing items for the static variables was below 20%, the percentage of missing items for the dynamic variables collected over three assessment waves exceeded this criterion. As a result, the dynamic PANAS affect variables were subsequently pro-rated for up to three missing items to retain as much data as possible. While a higher proportion of missing data can be expected in any multi-wave study that requires repeated participation over time, it is also important to note that this issue is perhaps even more prevalent for corrections-based multi-wave research of adults in the community on probation. This is due to the considerable variations of life circumstances for this particular cohort over time, making research follow-up and ongoing voluntary participation even more precarious. Regardless, several attempts to decrease the amount of missing data in this study were made through multiple targeted research design measures, e.g., by implementing an increasing financial incentive for each subsequent participation, by presenting study questionnaire items in a randomised order to combat any systematic patterns of data missing due to question fatigue, and by selecting statistical analyses (multilevel modelling and Cox regression survival analysis) that allowed for unbalanced data structures.

A limitation related to the PANAS scales used to assess dynamic affect was that all

PANAS scale items assessed the amount and frequency of affect as it was experienced by the participants over the last 14 days (i.e. "Please indicate how much you have been feeling this way during the last two weeks"), on a 5-point Likert scale, ranging from: 1- 'not at all' to 5- 'very much'. As such, the PANAS scale did not assess the potential intensity and/or strength of the affect that was experienced. This feature limits the generalisability of findings to self-reported affective frequencies only.

Another limitation was that the final participant sample was comprised of individuals from two smaller subsamples who were recruited from a Texas state probation agency and an Oklahoma state federal probation agency. Given that these two participant subsamples originated from two different geographical locations, it remains possible that significant differences exist between the two subsamples, which could in turn suggest that combining the two subsamples was inappropriate. However, the total sample size was not large enough to conduct analyses separately from data from each separate location.

The relatively low recidivism outcome rates (i.e., 54 recidivism outcomes for a total of 352 participants, or 15.3%) also limited the statistical power of the analyses used in this study to detect prediction effects related to recidivism outcomes. The overall low recidivism rates in the current sample were most likely a natural consequence of study participants belonging predominantly to the low to moderate recidivism risk categories. The recidivism rates would have likely been higher if the study sample had retained a larger proportion of high recidivism risk participants.

Furthermore, variations in recidivism risk assessments tools used between the two participant subsamples were also a limiting factor. Although the recidivism risk assessment tools used in this study were ultimately considered suitably equivalent due to the similarity of their risk assessment domains, the two recidivism risk tools were also different enough that risk scores could not be directly compared. This distinction subsequently limited the potential to directly contrast the current sample risk information with previous research by Brown et al (2009).

Further, all repeated measures study designs are inherently susceptible to learning-over-time and carry-over effects; therefore, it is possible that some of the dynamic changes noted were partially due to the increased familiarity with the test questions. However, due to the research design employed, this is considered highly unlikely in the current study. Firstly, we sought to minimise chances of any learning effects by randomising the order of questions, as well as by introducing a self-directed questionnaire topic choices from session to session. For example, participants in the current study were encouraged to make independent choices throughout each participation session regarding which group of questions (e.g., “thoughts about myself”, “how I’m feeling”, etc.) they would like to answer next. Moreover, within each question group, the items were presented in a newly randomised order on each participation occasion, thus further reducing any potential for learning by repetition. Ultimately, any carry-over learning effects were further diminished due to the relatively large volume of questions given to each participant at each assessment point (i.e., 285 unique questionnaire items, inclusive of other questionnaires not used for the purposes of this study). Such a large number of questions at each assessment wave would have decreased the likelihood that participants remembered their previous answers for any particular question item, from one assessment session to another.

It is also important to mention is that the current study participant sample was limited to adults who were on community probation for predominantly non-violent offences, such as driving under influence of substances and other non-violent crimes, with most (64.1%) of the sample belonging to the moderate recidivism risk category, with an additional 24.6% belonging to the low risk category. As a consequence, the results of this study may not generalise to other correctional populations which may also be of research interest, such as individuals who violently offend, forensic patients, or forensic youth populations.

Although the Introduction chapter has outlined desistance and its principles in detail, this research study had not measured any desistance outcomes directly, which is another limitation of this study. Our outcome variable was recidivism. We did however consider desistance and recidivism as two opposite sides of the same coin – so that presence of one outcome (e.g. recidivism) automatically indicated the absence of the other outcome (desistance) at that time point. Conversely, an absence of a recidivism event has indicated ongoing desistance at that time point.

Finally, this study was an exploratory analysis focused on prediction of recidivism outcomes. Like all prediction research, it requires cross-validation via future research involving both similar and different correctional samples, to ascertain both the validity and the generalisability of the current findings.

Directions for Future Research

Before suggesting potential directions for future research, it is important to highlight the relative paucity of any existing research on affect in correctional populations. While the results of the current study would encourage the view that dynamic positive and negative affect could be important variables to further explore and consider for predicting risk of recidivism over time, this first necessitates that future researchers purposefully incorporate self-reported affect measures into their study design, so potential links with recidivism risk could be further explored. In other words, until self-reported assessment of affect becomes a more common-place practice in future correctional research designs, we will simply not have the access to the appropriate information to investigate the links between affect and recidivism rates in more detail.

It is also important to consider the relative accuracy of measuring affect via a subjective self-report scale (such as PANAS), as opposed to the objective observational assessments that are often relied upon in correctional settings. Arguably, if the self-report questionnaire is simple to understand and answered honestly, its ratings can provide a more accurate and nuanced insight into individuals' internal affective experiences, as opposed to observational ratings of a typically minimal number of facets of individuals' affective repertoire (e.g., proneness to anger, behavioural expression of internal sadness) competed by probation officers. More frequent use of self-report affect measurement tools in future correctional research may be important, as individuals may internally feel emotions such as anger or happiness, however, for a variety of conscious or unconscious influences (e.g., personality traits, family upbringing, cultural conditioning or social desirability effect, etc.), they may not be able or willing to overtly display or discuss their affective states with others (including correctional staff). Limited affective expression in correctional settings could result in failure to detect relevant emotional experiences through observational ratings only, which is still the most common way of collecting affect-based data in correctional research.

Further research is also needed before any potential interventions focused on positive and negative affective experiences may be initiated to attempt to reduce adult recidivism based on the results of this study. Although the current study results are promising toward suggesting positive emotions may be increased as a pathway towards lowering overall recidivism risk of adults on probation, we would not support quick application of short-term, feel-good interventions without advocating for further research and a very nuanced understanding of the current study's complete findings, its limitations and further study results. For example, the current study results indicated that high recidivism risk participants consistently reported a significant rise in their average positive emotions over time on probation, which was in direct contrast to low-to-moderate risk cohort's relative stability of positive emotions over time on probation. This finding would suggest that, aside from having a higher self-reported frequency of positive affect experiences, another relevant factor for reducing the risk of recidivism could be the individuals' overall ability to maintain the stability of their emotions over longer periods of time. Skills developing this emotional maturity is generally not easily achievable via short-term, positive affect-boosting interventions.

Another reason for exercising caution around implementing novel interventions without further research is that well-intended positive affect interventions in correctional populations have potential to backfire in relation to individuals' recidivism outcomes. For example, in Wormith's (1984) study of 50 incarcerated individuals, participants who self-reported improved self-esteem after attending a group treatment with trained volunteers were also more likely to re-offend compared to those who reported decreased self-esteem following treatment. In other words, although evidence from this study suggested the intervention effectively helped attendees feel increasingly better about themselves, their increased self-esteem did not translate into reduced recidivism risk, but quite the contrary. Furthermore, this result was particularly true for those offending individuals who had strongest attachment to their offending identity, pointing towards the conclusion that recidivism rates are likely to be influenced by a complex equation of individual characteristics, types of interventions offered and the wider environmental circumstances around each individual (Wormith, 1984). It is also likely that perhaps not all types of positive affect have equal potential for being associated with or contributing to reductions in recidivism likelihood. Further, different individuals are likely to respond differently following interventions based on their individual and environmental circumstances. Further research is necessary to inform a more nuanced approach to any future intervention planning with regards to positive affect interventions.

Regarding general future research directions that could follow on from the findings of the current study, it is recommended that the current study design is replicated in a larger correctional sample of adults on probation to attempt to replicate and validate the current study results. Conducting similar research to explore the value of positive and negative affect to predict recidivism outcomes in alternative cohorts of interest is also recommended, e.g., individuals who violently offend, youth who offend, females who offend and forensic hospital patients. In particular, further research on the relationship of positive and negative affect with recidivism risk in youth forensic samples may be of particular interest for increasing understanding of a critical risk cohort with high recidivism rates and low likelihood of emotion regulation skills. It is possible that by deepening knowledge of the interplay between dynamic affect and recidivism risk in youth who offend, and by adjusting intervention efforts, we may also increase youth offenders' prospects to cease re-offending behaviours sooner in life.

Another potential future research direction of interest could be a more in-depth dynamic investigation of specific emotions, both positive and negative, and their connection with risk of reoffending. For example, previous theory and research on emotions and offending had identified anger (Daffern et al., 2005; Novaco, 2011) and shame (Braithwaite, 1989; Harris, 2006) as particularly important negative emotions that influence the risk of recidivism. The Reintegrative Shaming Theory further suggests that a particular type of shame – reintegrative shame – may be an important component toward reducing risk of recidivism (Braithwaite, 1989; Braithwaite & Mugford, 1994). However, exploratory analysis of shame, anger or any other singular emotions was not within the scope of this thesis. It is also recommended that future researchers who may be interested in investigating singular emotions also consider utilising a more fine-tuned, nuanced self-report measure of those emotions than the PANAS provided in this study. It is not ideal to use a single 5-point scale item to investigate a core construct of interest.

Furthermore, in the light of the frequent mismatch between the overrepresentation of people from cultural minorities in prison settings versus their representation in the general community, it might also be useful to investigate the affective patterns for populations of individuals who offend from different cultural backgrounds, who may view, value and manage dimensions of their affective expression differently. It is also likely that a variety of factors may influence affective expressiveness across different cultures. For example, previous cross-cultural research revealed that emotionally expressive behaviour appears partially determined by the level of heterogeneity existing within a specific culture, i.e., the levels of multiculturalism within a specific culture (Rychlowska et al., 2015). Other cross-cultural research on differences between individualistic and collectivistic cultures has shown that differences in emotional expressivity levels across culture types can significantly influence others' perceptions of an individual's level of social competence (Louie, Wang, Fung, & Lau, 2015). This finding may be relevant in the context of correctional staff routinely rating proneness to anger or other recidivism risk factors based on their own perceptions of the life circumstances and personality of the individual being assessed.

Specifically among people characterised as ethnic minorities, De Maesschlack et al. (2011) found that the levels of emotional expressivity of ethnic minorities during primary healthcare consultations were influenced by several factors, e.g., their cultural background (i.e., whether they are used to talking to authority figures about their emotions), their acculturation levels (i.e., whether they had enough time to be acculturated to talking to authority figures about their emotions), and their proficiency in their second language (i.e., whether minority individuals were able to express their emotions adequately in their acquired language). In particular, significantly fewer affective cues were observed in video recordings of consultations with individuals who had poor acquired language proficiency (De Maesschalck, Deveugele, & Willems, 2011). This suggests that low language proficiency may also manifest as a reduced affective expression during communication, which may be relevant to consider among culturally and linguistically diverse groups of adults who offend. Additionally, previous research related to incarcerated offending populations revealed a tendency for prisoners to intentionally mask their affective expressivity as a likely consequence of traumatic life histories or perceived need to supress emotional expression as an adaptive response to the hyper-masculine prison culture which strongly discourages displays of emotional vulnerability (Laws, 2019). The accumulation of traumatic life experiences appears to be particularly relevant among Indigenous Australian prison populations, as people from these cultural groups consistently report higher levels of trait anger and more frequent experiences of trauma symptoms, including both childhood trauma and intergenerational trauma (Danieli, 1998; Day et al., 2008).

Aside from cultural differences, it would also be beneficial for future research to further explore different dynamic patterns of positive and negative affect specifically among people assessed as having high recidivism risk, while continuing to compare findings to results from lower recidivism risk participants. The current study results indicated a possibility that high recidivism risk category participants represent a significantly different correctional population with regards to their dynamic affective patterns, which could ultimately have important implications for the assessment, treatment and ongoing management of this particular cohort.

Similarly, another further research avenue to explore could be whether any significant patterns related to dynamic affect and recidivism would emerge for adult female correctional populations, given that females are often considered a separate (and perhaps more complex) population within correctional research, largely due to their higher overall experiences of past and ongoing trauma, stressors, interpersonal violence and mental health issues.

Chapter Six: Conclusion

Correctional research has predominately focused on exploring the links between cognitions and recidivism, rather than the links between emotions and recidivism. While this may be partly due to the political and /or operational constraints regarding what is considered relevant or ethical research in populations of individuals who offend, this trend has also been influenced by the long-term research emphasis on investigating cognitions as direct precursors of behaviours, with affect being conceptualised as a less relevant by-product of individual's cognitions (Lazarus, 1984).

A previous study by Brown et al (2009) pioneered exploration of the predictive ability of dynamic positive and negative affect states in relation to re-offending outcomes for adults on probation (Brown et al., 2009). Following their work, the current study represents: (i) the first known attempt to replicate some of Brown et al.'s (2009) affect-related findings, and (ii) the first known attempt to further explore the predictive value of dynamic positive and negative affect in relation to recidivism for adults on probation for up to 12-18 months, by also considering both valence and behavioural activation affect dimensions, positivity ratio, as well as static risk factors such as participants' age, gender and recidivism risk category.

Consistent with previous research, the current study results demonstrated that negative affect is a significant dynamic predictor of recidivism when considered independently. However, current analyses further revealed that when individual recidivism risk category was controlled, the overall predictive power related to dynamic negative affect was adequately accounted for by standard risk of recidivism assessment tools. Surprisingly, this finding did not apply to highly activating dynamic negative affect (i.e., feeling uptight, angry, ashamed, stressed, nervous, guilty, and irritable) which remained a significant predictor of recidivism outcomes even when controlling for recidivism risk category. This is an interesting and novel finding that points towards the theoretical importance of highly activating negative affect, over and above low activating or overall negative affect, and the potential utility of specifically measuring high activation negative affect in future efforts to improve prediction of adult recidivism.

As a further significant and unique contribution to the criminology field, the current study results also demonstrated that dynamic positive affect in general, and the low activation dimension of positive affect in particular (e.g., feeling calm, content, relaxed) emerged as significant dynamic predictors of recidivism. Prediction effects remained independently of the presence or levels of the dynamic negative affect and participants' recidivism risk category. This is a significant novel finding in this field which points towards the importance of assessing adult probationers' dynamic positive affect, which is currently not accounted for by standard recidivism risk assessment tools to improve recidivism predictions for this population.

Moreover, the cohort of people assessed as having high recidivism risk displayed significantly higher increases in positive affect and near significant faster decreases in negative affect over time on probation, compared to low-to-moderate recidivism risk participants in the current study. This finding suggests that high recidivism risk adults may represent a theoretically important group that is significantly different from both the average correctional population, as well as from average non-correctional populations, in terms of having distinct patterns of positive and negative affect change over time. This result was also in direct contrast with the overall stability of average positive and negative emotions over time that was seen in the low to moderate risk group. This is another novel finding related specifically to high recidivism risk adults in correctional research, which requires support of subsequent research to establish its validity.

Finally, the current study found that the PANAS positivity ratio did not emerge as a significant predictor of recidivism, over and above its individual components, for this participant sample. This finding suggests that a simpler model, inclusive of affective components only, is perhaps a more meaningful and useful way of exploring predictions of recidivism outcomes for adults on probation.

When considered together, the current study results strongly suggest that adults who offend dynamic affective experiences on probation matter toward improving our ability to predict recidivism outcomes and potentially understand the human experiences that drive people back into crime while on probation. Further research that includes total positive affect, low activating positive affect and highly activating negative affect when investigating time to recidivism is needed to validate the current results and to further explore the generalisability of the current study findings across both similar and different correctional samples.

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Appendices

Appendix A. Ethics Approval

From: **Astrid Nordmann** anordmann@swin.edu.au
Subject: SHR Project 2017/224 - Ethics clearance
Date: October 2, 2017 at 2:03 PM
To: Caleb Lloyd cdlloyd@swin.edu.au
Cc: RES Ethics resethics@swin.edu.au

AN

To: Dr Caleb Lloyd, FHAD/CFBS

Dear Dr Lloyd,

SHR Project 2017/224 – Research on Offender Decision-Making and Desistance from Crime (Longitudinal Phase)
Dr Caleb Lloyd, FHAD/CFBS
Approved duration: 03-10-2017 to 03-10-2022 [adjusted]

I refer to the ethical review of the above project protocol by Swinburne's Human Research Ethics Committee (SUHREC). Your response to the review, as emailed on 30 September 2017, accords with the Committee review.

I am pleased to advise that, as submitted to date, the project may proceed in line with standard on-going ethics clearance conditions outlined below.

- The approved duration is **03 October 2017** to **03 October 2022** unless an extension request is subsequently approved.

- All human research activity undertaken under Swinburne auspices must conform to Swinburne and external regulatory standards, including the *National Statement on Ethical Conduct in Human Research* and with respect to secure data use, retention and disposal.

- The named Swinburne Chief Investigator/Supervisor remains responsible for any personnel appointed to or associated with the project being made aware of ethics clearance conditions, including research and consent procedures or instruments approved. Any change in chief investigator/supervisor, and addition or removal of other personnel/students from the project, requires timely notification and SUHREC endorsement.

- The above project has been approved as submitted for ethical review by or on behalf of SUHREC. Amendments to approved procedures or instruments ordinarily require prior ethical appraisal/clearance. SUHREC must be notified immediately or as soon as possible thereafter of (a) any serious or unexpected adverse effects on participants and any redress measures; (b) proposed changes in protocols; and (c) unforeseen events which might affect continued ethical acceptability of the project.

- At a minimum, an annual report on the progress of the project is required as well as at the conclusion (or abandonment) of the project. Information on project monitoring and variations/additions, self-audits and progress reports can be found on the Research Ethics Internet pages.

- A duly authorised external or internal audit of the project may be undertaken at any time.

Please contact the Research Ethics Office if you have any queries about on-going ethics clearance, citing the Swinburne project number. A copy of this email should be retained as part of project record-keeping.

Best wishes for the project.

Yours sincerely

Astrid Nordmann
Secretary, SUHREC

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Appendix B. Positive Affect Negative Affect Schedule (PANAS)

Positive Affect Negative Affect Schedule (PANAS)
(Watson & Tellegen, 1988)

This questionnaire consists of a number of words that describe feelings and emotions. Please indicate how much you have been feeling this way during the past two weeks. The best way to do this is to answer each question quickly without much thought. If you have any questions about the meanings of any of these words please ask!

Use the following scale to describe the way you feel:

[redacted]

____ interested	____ active	____ nervous
____ up tight	____ quiet	____ miserable
____ calm	____ enthusiastic	____ strong
____ hopeless	____ depressed	____ bored
____ at ease	____ content	____ guilty
____ numb	____ inactive	____ sad
____ angry	____ sleepy	____ unhappy
____ alert	____ proud	____ relaxed
____ ashamed	____ stressed	____ tired
____ excited	____ peaceful	____ irritable

Now that we've gone through the list, which of these do you think is the strongest single feeling that you've had in the last two weeks?

(fill in) ______________________

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Scoring instructions

To score the Positive Affect, one would add up the scores on lines 1, 3, 5, 9, 10, 12, 14, 16, 17 & 19.

Scores may range anywhere from 10 – 50. Higher scores represent higher levels of positive affect. Mean scores: momentary = 29.7 and weekly = 33.3.

To score the Negative Affect, one would add up the scores on items 2, 4, 6, 7, 8, 11, 13, 15, 18 & 20.

Scores may range anywhere from 10 – 50. Higher scores represent higher levels of negative affect. Mean scores: momentary = 14.8 and weekly = 17.4.