Using remote monitoring to improve prediction and develop understanding of aggression in inpatient mental health services

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Abstract

Inpatient aggression in forensic mental health services has serious negative consequences for both staff and service users. Methods of monitoring and predicting risk of aggression are typically based on changeable dynamic risk factors. Previous research shows that risk assessments are typically inaccurate, particularly for events when aggression escalate rapidly. One reason for this is that these assessments are carried out infrequently and cannot capture short-term change in relevant risk factors. These assessments are also limited to staff-reported observable variables and cannot capture the psychophysiological deregulation which neurophysiological theories suggest are relevant to the risk of aggressive behaviour. Developments in experience sampling methods and passive remote monitoring technology now enable these dynamic variables to be measured over extended periods of time in participants' typical daily environment with limited intrusion in their daily activities. Across five empirical studies the overall aim of this thesis was to investigate whether monitoring relevant dynamic risk factors frequently could predict inpatient aggression short time periods. A systematic review was conducted (Chapter 2) which identified 26 candidate dynamic risk factors in forensic mental health services for inclusion in subsequent studies in this thesis. A series of qualitative focus groups was then conducted with forensic mental health nursing staff (Chapter 3), which highlighted potential clinical benefits of remote monitoring in addition to challenges that would need to be overcome. Two pilot studies with service users and staff were then carried out (Chapters 4 and 5), which confirmed the acceptability of remote monitoring in forensic services and identified optimal timeframes for identifying change in dynamic risk factors. An empirical study was then conducted (Chapters 6, 7 and 8) with forensic mental health service users to investigate whether short term changes in dynamic risk factors were associated with future aggression. Findings from these studies identified a number of psychological and psychophysiological risk factors relating to Positive and Negative Affect, Aggression Ideation, Phasic Electrodermal Activity and reduced Heart Rate Variability which significantly predicted acts of physical and verbal aggression up to 40-minutes before the aggressive outcome was observed. These findings point to a window opportunity between the onset of a particular risk factors and occurrence of aggression in which effective and targeted intervention and support may avert the aggressive incident.

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List of Abbreviations

AIHQ	Ambiguous Intention and Hostility Questionnaire
ANOVA	Analysis of Variance
ANS	Autonomic Nervous System
BIS/BAS	Behavioural Inhibition System/Behavioural Activation System
BPRS	Brief Psychiatric Rating Scale
DASA	Dynamic Appraisal of Situational Aggression
DPD	Dissocial Personality Disorder
DSM - IV	Diagnostic and Statistical Manual, 4th Edition
DSM - V	Diagnostic and Statistical Manual, 5th Edition
EDA	Electrodermal Activity
ESM	Experience Sampling Methodology
GLM	Good Lives Model
HCR-20	Historical Clinical Risk Management-20
HRV	Heart Rate Variability
Hz	Hertz
ICD - 10	International Classification of Diseases, 10th Revision
IQ	Intelligence Quotient
MOAS	Modified Overt Aggression Scale
NHS	National Health Service
PCL-R	Psychopathy Checklist – Revised
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PROSPERO	International Prospective Register of Systematic Reviews
RMSSD	Root Mean Square of Successive Differences
RNR	Risk Need Responsivity Model
SCL	Skin Conductance Level
SCR	Skin Conductance Response
SDNN	Standard Deviation of Normal-to-Normal Differences
SLaM	South London and Maudsley NHS Foundation Trust
SNS	Sympathetic Nervous System
TEIQue-SF	Trait Emotional Intelligence Questionnaire – Short Form

TMT	Trail Making Task
WTAR	Wechsler Test of Adult Reading

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Chapter 1 : Introduction

1.1 Mental Health and Aggression

Most people who experience mental health difficulties are not aggressive (Walsh et al., 2003), and large longitudinal cohort studies have illustrated that having a diagnosed mental health difficulty is associated instead with a significantly greater risk of being a victim of aggression than individuals with no diagnosis (Dean et al., 2018; Sariaslan et al., 2020). However, the inaccurate media portrayals of the link between mental health and aggression (Bowen et al., 2019) has contributed to the stigma faced by those with mental health difficulties (Strassnig et al., 2020). Previous research has operationalised the terms 'violence' and 'aggression' differently, for example, including physical acts against another person but excluding verbal threats (Sedgwick et al., 2016b). Consistent with recommendations to consider the various forms that this behaviour can take (Harris et al., 2013), and to avoid a narrow definition encompassing only physical bodily harm, the term 'aggression' is used throughout this thesis. For those who do commit aggressive acts there is a large body of evidence establishing a significant association between some mental health difficulties and aggressive behaviour (Fazel et al., 2009b; Joyal et al., 2007) . Of these, the two categories of mental health difficulty commonly encountered at the interface between mental health services and the criminal justice system are schizophrenia-spectrum conditions and dissocial/antisocial personality disorder.

1.1.1 Schizophrenia-Spectrum Conditions

Schizophrenia-spectrum conditions include a number of diagnoses including schizophrenia, schizoaffective disorder and delusional disorder and represent one of the leading causes of disability internationally (Vos et al., 2017). The lifetime prevalence of schizophrenia-spectrum conditions is estimated at 2-3% (Perälä et al., 2007), while approximately 6% of individuals experience sub-clinical levels of psychotic experiences which do not meet the diagnostic threshold for a schizophrenia-spectrum condition (Linscott & van Os, 2013). These conditions are characterised by a range of symptoms including abnormal thoughts and sensory experiences (positive symptoms), diminished motivation, experience of pleasure and emotional expression (negative symptoms; Howes & Murray, 2014). Cognitive difficulties are also a common feature of these conditions (Cella et al., 2020), and individuals may experience difficulties in domains such as memory, attention, executive function and

processing speed compared to general population averages (Bora et al., 2017; Reichenberg & Harvey, 2007). Social cognitive difficulties, such as emotion processing, attributional biases and social perception (Green et al., 2019) are another important and common feature of schizophrenia-spectrum conditions, which have a significant impact on real-world social functioning even after controlling for other cognitive difficulties (Fett et al., 2011). Overall the range of difficulties associated with schizophrenia-spectrum conditions can have a significant negative effect on individuals' everyday functioning (Allott et al., 2011)

1.1.1.1 Association with Aggression

Consistently reported, modest, but significant, associations have been found between schizophrenia-spectrum conditions and aggression. Interpreting this relationship can be complicated because of the different aggressive outcomes used, ranging from criminal conviction for aggressive offences to aggressive acts committed in the community or prison/hospital services (see the Aggression in Inpatient Mental Health Services Below for a review). Two meta-analyses reported that the odds of being convicted for an aggressive crime (Fazel et al., 2009a) and/or behaving aggressively in the community or institutional settings (Douglas et al., 2009) were up to seven time higher among those with schizophrenia-spectrum conditions compared to general population controls. Base rates of aggression were relatively low at 1.6% however, indicating that aggression is still uncommon even with the additional risk conferred by schizophrenia-spectrum conditions. There was also significant heterogeneity in the reported effect sizes in these studies. Fazel et al. (2009a) reported that the increased risk of aggression appeared to be predicted by substance abuse, with no significant differences in risk of aggression observed between those with substance abuse alone versus those with comorbid schizophrenia-spectrum conditions and substance abuse. Douglas et al. (2009) also concluded that that the increased risk arising from schizophrenia-spectrum conditions was like that of other established risk factors, such as previous aggression.

Similar findings have been reported in longitudinal investigations using national registry data. After adjusting for substance abuse, schizophrenia-spectrum conditions were associated with a three- (men) and seven-fold (women) increased risk of conviction for an aggressive offence (Stevens et al., 2015). Fazel et al. (2009b) also reported that schizophrenia-spectrum conditions were associated with a significantly increased likelihood of conviction for an aggressive crime, compared to non-affected individuals, with comorbid substance abused conferring significantly greater risk. When controlling for genetic and/or shared environmental factors through comparisons with unaffected siblings, the relationship

between substance abuse and aggression was significantly reduced. Another investigation using the Swedish national registry data (Fazel et al., 2014) indicated that, within five years of receiving a schizophrenia-spectrum diagnosis, 11% of men and 3% of women had been convicted of an aggressive crime, but that substance abuse, previous convictions and self-harm were also predictive of this outcome. Schizophrenia-spectrum conditions therefore constitute an important, but partial, contribution to the risk of aggression and specifically conviction for an aggressive crime, with substance abuse contributing significantly towards this increased risk.

1.1.1.2 Aetiology of Aggression

The pathways from schizophrenia-spectrum conditions to aggression may also arise due to factors other than substance abuse, such as positive symptoms. In a longitudinal cohort study of individuals living in the community following release from prison, Keers et al. (2014) reported that persecutory delusions were associated with a three-fold increase in the risk of aggression, though this relationship was only observed among individuals with schizophrenia-spectrum conditions who were not receiving treatment. Similarly, Swanson et al. (2006) reported that persecutory delusions were significantly associated with both minor and serious aggression in the community. Compliance with command hallucinations has also been significantly associated with aggression in community and inpatient services (Shawyer et al., 2008), with this relationship predicted by the presence of congruent delusions. Cognitive difficulties have also been implicated in the link between schizophrenia-spectrum conditions and aggression, though research findings are mixed (Weiss, 2012). For example, in one study poor performance in measures of executive function significantly predicted aggression over a 12-week period among inpatients (Krakowski & Czobor, 2012). O'Reilly et al. (2015) reported that deficits in social cognition were significantly associated with aggression, independent of symptom severity. Jones and Harvey (2020) also reported that social cognition training was associated with significant reductions in aggressive ideation and behaviour. However, a systematic review and meta-regression by Witt et al. (2013) failed to find any significant associations between cognition and aggression.

Reasons for aggression among individuals with schizophrenia-spectrum conditions are likely to differ. Volavka and Citrome (2008) suggest three key drivers for aggression: i) positive symptoms, ii) impulsivity and iii) comorbid personality disorder and particularly psychopathy (see section on personality disorder below). Similarly Bo et al. (2011) propose two distinct trajectories towards aggression in schizophrenia-spectrum conditions driven by positive symptoms or comorbid personality disorder and psychopathic traits. Alternative frameworks

to account for the heterogeneity in how aggression manifests among individuals have proposed subtypes based on the age of onset of the individuals' aggressive behaviour (Richard-Devantoy et al., 2013). For example, Hodgins (2008) suggest a subtype of 'early start' offenders with aggression observed prior to illness onset and largely stable throughout life, driven by risk factors known to be associated with antisocial behaviour such as socioeconomic status and childhood abuse. In the second and largest subtype, known as 'late start' offenders, aggression coincides with illness onset and is influenced by vulnerability to substance use. A third subtype is comprised of individuals who demonstrate no aggression for decades after illness onset but then engage in serious acts of aggression in response to symptoms (e.g. persecutory delusion or command hallucinations).

1.1.2 Dissocial Personality Disorder

Dissocial personality disorder (DPD) is a personality disorder characterised by an overall disregard for social norms and the rights of other people. A number of specific personality traits are evident and include a callous disregard for the feelings of others, a low tolerance for frustration and consequential low threshold for aggression, a tendency to blame others or rationalize behaviour, and an inability to modify behaviour in response to punishment or other adverse experiences (World Health Organisation, 1992). Symptoms of DPD tend to begin in childhood where a diagnosis of conduct disorder may be given (DeLisi et al., 2018), and persist into adulthood. The lifetime prevalence of DPD has been estimated at 1-5% (Ogloff, 2006; Werner et al., 2015), with men three times more likely to develop DPD than women (Alegria et al., 2013). A larger body of research used the DSM-V (American Psychiatric Association, 2013) classification of antisocial personality disorder rather than DPD (ICD-10; WHO, 1992), with the main differences including a greater emphasis on interpersonal difficulties over antisocial behaviour in the ICD (NICE, 2010). However, subsequent revisions of the DSM led to a concordance in the criteria across these two diagnostic systems and there is now significant overlap. Both DPD and antisocial personality disorder are associated with significant impairment in individuals' day-to-day lives and future prospects (Black, 2013), therefore consistent with previous research (e.g. Sedgwick et al., 2017) the antisocial personality disorder literature will also be discussed in this thesis.

1.1.2.1 Association with Aggression

Dissocial personality disorder is overrepresented among forensic populations. A meta-analysis of over 23,000 prisoners reported that 47% of men and 21% of women met diagnostic criteria for DPD, a 10-fold increase compared to rates in the general population (Fazel & Danesh, 2002). High rates of DPD have also been reported in forensic mental health

services. For example, Coid (2003) reported a prevalence of approximately 55% in high-secure services in the UK. Dissocial personality disorder is also strongly associated with community aggression and crime. In England and Wales over a 10 year period, 16% of homicides were committed by an individual with DPD (National Confidential Enquiry for Suicide and Homicide, 2014). It was estimated from a household survey of over 8,000 UK individuals that 24% of the risk of community aggression was attributable to DPD (Coid et al. 2006). Prospective studies have also shown dissocial personality disorder to be predictive of future aggression in inpatient settings. A retrospective review of over 500 service users in a forensic mental health service reported that the risk of engaging in aggressive behaviour in the previous year was double that for individuals diagnosed with DPD, compared to non-affected individuals (Lussier et al., 2009). Multiple studies have also reported that rates of aggressive reoffending following discharge from forensic mental health services are significantly higher, and occur over a shorter period of time among those with DPD (Coid et al., 2007; Howard et al., 2013).

1.1.2.2 Psychopathy

Psychopathy shares many characteristics with DPD and may account for some of the association between DPD and aggression (Ogloff, 2006). Psychopathy is characterised by personality traits reflecting a lack of empathy and remorse, superficial and manipulative interpersonal styles, impulsivity and antisocial behaviour (Hare, 2003). Approximately 32% of those who meet diagnostic criteria for DPD also reach the clinical cut off for psychopathy (Coid & Ullrich, 2010), while 80% of those meeting criteria for psychopathy also meet criteria for DPD (Hildebrand & de Ruiter, 2004). Individuals with DPD and comorbid psychopathy may constitute a distinct subtype, with one study reporting forensic mental health service users with comorbid DPD and psychopathy had a history of more severe aggression and emotion deregulation than those with DPD alone (Kosson et al., 2006). Evidence is mixed however, with other studies finding no significant differences between comorbid DPD and psychopathy and DPD alone in either cognition (De Brito et al., 2013; Zeier et al., 2012) or demographics. It has been suggested that psychopathy may not represent a distinct subtype but reflect a variant of DPD associated with more severe difficulties (Coid & Ullrich, 2010).

1.1.3 Aggression in Inpatient Mental Health Services

The relationship between mental health and aggression is particularly important within inpatient mental health services, where its presence and absence determines admission and discharge from these services (Stahl, 2014). Prevalence of aggression varies considerably

across studies, influenced by factors such as whether the service is a civil or forensic mental health service[1] and how aggression is operationalised. Verbal aggression is typically more prevalent than physical aggression towards others. For example, Renwick et al. (2016) reported that over an eight month period 51% of patients in civil mental health services displayed verbal aggression on at least one occasion, with 20% displaying physical aggression towards others in the same period. Rates of aggression can also vary according to how long service users have been in contact with services, for example, Barlow et al. (2000) reported that aggression was most common within the first two days of admission. Most research on aggression in inpatient mental health services has been conducted in countries categorised as high-income, therefore it is unclear how prevalence of aggression differs according to socioeconomic status between countries. For example, low- to middle-income countries account for 90% of aggression-related deaths (Matzopoulos et al., 2008) therefore rates of aggression within inpatient mental health services may differ to those of higher-income countries. Lower socioeconomic status within countries have also been associated with increased risk of violence (Chen et al., 2013), and again it is unclear from previous research how within-country disparity in socioeconomic status may affect rates of aggression in inpatient mental health services.

A meta-analysis of aggression prevalence in civil mental health services by Iozzino et al. (2015) reported that 17% of service users committed at least one act of aggression during their treatment. Higher rates were reported in men, those who were involuntarily detained, and schizophrenia-spectrum conditions. A recent meta-analysis by di Giacomo et al. (2020) reported a similar pooled prevalence of aggression of 18% but noted significant heterogeneity which potentially affected their conclusions. Moderator analysis indicated that the between-study heterogeneity was explained by the proportion of men within the study (18% of heterogeneity), the proportion of involuntary service users (13%) and comorbid substance use (36%). These are common characteristics of forensic mental health services and these may explain why rates of aggression can be higher compared to civil services. For example, in one mixed gender Dutch forensic mental health service, over a five year period, 3,713 aggressive incidents were reported of which 469 were physical aggression

[1] In the UK, forensic mental health services provide care and support for individuals with mental health difficulties who have and/or continue to pose a risk of harm to themselves or others as a result of their mental health difficulties (Joint Commissioning Panel for Mental Health, 2013).

(Verstegen et al., 2020). Sixty percent of service users exhibited at least one form of aggressive behaviour during this period, with 22% exhibiting physical aggression. Typically, a small proportion of service users[2] account for a large proportion of aggressive incidents. For example, Lussier et al. (2009) reported that of 527 service users in a forensic menta health service 10% were responsible for over 60% of aggressive incidents recorded over one year.

1.1.3.1 Impact of Inpatient Aggression

Aggression in inpatient mental health services has negative consequences for everyone involved. Members of nursing staff are often the targets of inpatient aggression, with one study reporting that staff were the targets of 57% of all aggressive incidents recorded (Foster et al., 2007). Studies have consistently reported that exposure to inpatient aggression has a negative impact on the psychological and physical wellbeing of staff (Renwick et al., 2019). In one staff survey, Lee et al. (2015) reported that 36% of staff experienced significant difficulties in a measure of general distress (the General Health Questuionnaire-28, Goldberg & Williams, 1988). Additionally, up to 17% met diagnostic criteria for post-traumatic stress disorder. Husum et al. (2020) conducted a mixed-methods study exploring staff members' experience of inpatient aggression. Over 70% of staff had been subject to verbal aggression at least once during their course of work , which they reported led to feelings of intimidation, fear, and vulnerability. While they highlighted that these were not necessarily daily experiences, staff did report feeling that these experiences were an inevitable part of their profession. These staff experiences are also not novel characteristics of working in inpatient mental health services but have been consistently identified over time (Whittington, 1994). Exposure to aggression has also been shown to contribute to absenteeism. In one study, over 20% of nursing staff reported being unable to work for at least one day during the previous year as a result of inpatient aggression, with an average of 5.2 days per nurse being lost (Nijman et al. (2005).

Studies on the effects of inpatient aggression on service users have reported similar findings. Gudde et al's. (2015) systematic review identified themes concerning fear, lack of control and breakdown of therapeutic relationships. As well as being a consequence of inpatient aggression, these themes were also reported to be antecedents of future aggression. In addition to the effects of being a victim of aggression, qualitative studies have investigated

[2] Previous research has variously referred to individuals with mental health difficulties and a history of aggression as service users, patients, offenders or mentally disordered offenders. The term service user is used throughout this thesis.

the effects of being subject to commonly used restrictive practices for perpetrators of inpatient aggression, such as seclusion and restrain. One systematic review reported that this was associated with feelings of neglect, vulnerability and worsening mental health (Askew et al., 2019). Similarly feelings of anxiety, fear and anger have also been reported (Soininen et al., 2016).

Forensic mental health services are high-cost services (McCrone, 2008) and inpatient aggression significantly contributes to the costs of operating these services. In the UK The annual cost of all aggression in forensic mental health services, based on staff time and resources required to manage incidents (e.g. seclusion and enhanced observation), has been estimated as £72.5 million (Flood et al., 2008). Verbal aggression emerged as the costliest form of aggression to manage, estimated at £10.5 million annually. As forensic mental health services are funded by taxation, the negative impacts of inpatient aggression in terms of operational costs are felt widely.

1.2 Assessing and Managing Inpatient Aggression

1.2.1 Theoretical Models

Forensic mental health services place significant emphasis on assessing and treating aggression in their day-to-day practice. The Risk-Need-Responsivity (RNR) model (Andrews et al., 1990) has been one of the most influential theoretical models for assessing and managing risk of aggression in forensic mental health services and consists of three principles (Andrews & Bonta, 2010). The ***risk*** principle proposes that treatment efforts should be matched to service users' level of risk (i.e. service users at the highest risk of aggression should receive the most intense level of treatment). The ***need*** principle states that characteristics of the service user which are: i) related to their risk of aggression and ii) changeable (dynamic risk factors, see section below) should be the primary focus of these treatment efforts. The ***responsivity*** principle highlights the need for empirically supported treatment models which should be tailored to service users according to their motivation, strengths, and abilities. The need principle is the core of the RNR model as it dictates which factors associated with recidivism should be targeted through treatment efforts (Ward & Willis, 2016).

The Good Lives Model (GLM) is another influential model of service user rehabilitation in the context of aggressive behaviour and shares some of features of RNR. It is a strength-based approach to rehabilitation, focussing on both the risk factors of an individual and developing their strengths (Laws & Ward, 2011). Aggressive behaviour represents flawed attempts to

secure important goals in life, with dynamic risk factors serving as barriers to these goals (Ward et al., 2011). Identifying and modifying these dynamic risk factors is therefore an important component of treatment.

1.2.2 Dynamic Risk Factors

One of the key contributions of models such as the RNR and GLM has been highlighting the role of dynamic risk factors. Various terms have been used to describe the characteristics of individuals and their environments which are associated with aggression, typically defined on the basis of whether or not they could be altered through intervention (Heffernan et al., 2019). The RNR model originally conceptualised these factors as risk status and risk state, now typically referred to as static and dynamic risk factors, respectively. Static risk factors relate to individual characteristics which are associated with aggression but fixed in time and unalterable. For example, previous aggression is a robust predictor of future aggression, but is not amenable to change. Dynamic risk factors on the other hand can be defined as variables which are associated with aggression and can change spontaneously or through intervention (Kraemer et al., 1997). Common examples include anger and negative affect, which is not stable over time and demonstrates fluctuations in intensity. The definition of dynamic risk factors change depending on whether they are considered causal factors for aggression, of which there is considerable debate (Ward & Willis, 2016). In addition to demonstrating evidence of change, Douglas and Skeem (2005) proposed that a causal dynamic risk factor should result in a concurrent increase or decrease in the risk of aggression when the risk factor is changed.

One of the key roles of establishing an individual's risk factors for aggression is to identify treatment targets and rehabilitative needs. While static factors are good predictors of aggression, they are unchanging and cannot reflect variations in risk level, therefore not represent valuable targets for treatment (Ward et al., 2011). Dynamic risk factors are a central component of treatment approaches in forensic mental health services, reflecting the assumption that reducing the intensity of dynamic risk factors, or eliminating them completely, will decrease the likelihood of future aggression. This approach reflects the ***need*** principle of the RNR model, specifically the recommendation that treatment should target changeable characteristics which are associated with aggression.

1.2.3 Risk Assessments

Dynamic risk factors also have an important influence on how inpatient aggression is assessed and managed. Risk assessments are routinely conducted in forensic mental health

services to determine an individuals' likelihood of engaging in aggressive behaviour in the future, and contemporary clinical guidelines specifically recommend the use of assessments which comprise dynamic risk factors (NICE, 2015), such as the Dynamic Appraisal of Situational Aggression (Ogloff & Daffern, 2006a) and Historical Clinical Risk Management-20 (Douglas et al., 2013). **Table 1** illustrates how risk assessments have developed from original unstructured clinical judgement, to contemporary assessments featuring dynamic risk factors.

Despite their frequency of use, there is considerable variation in the predictive accuracy for inpatient aggression (Mulder et al., 2016). For example, Coid et al's. (2011) evaluation of the three commonly used risk assessments reported that most items did not predict future aggression, though a small number of items did demonstrate a significant association. Meta-analyses have also reported variable predictive accuracy of commonly used assessments. In one analysis of over 23,000 forensic mental health service users, Fazel et al. (2012) reported low to moderate predictive accuracy, and assessed that, on the basis of this accuracy, an average of two service users would need to be detained to prevent one incident of aggression. Ramesh et al. (2018) evaluated the predictive accuracy of nine commonly used risk assessments and differentiated between those designed to predict risk over short time periods (e.g. two days or less), and those assessing risk over longer periods. Predictive accuracy was moderate for longer-term assessments but did demonstrate moderate to good accuracy over short time periods. This suggests that assessments of short-term aggression risk may offer more clinical benefit than assessments conducted in the long-term.

Table 1 Risk assessment typology

Type of Risk Assessment	Description
Unstructured Clinical Assessment	Assessments of risk are based on clinical training, experience, and anecdotal evidence. Provides flexibility by enabling the rater to select specific risk factors relevant to the individual. Susceptible to rater-bias and relevant risk factors may be missed.
Structured Actuarial Assessment	Fixed assessment procedure with numeric ratings for each risk factor providing a total risk score. Risk factors are derived from empirical research and correlated with aggression. Emphasis on static risk factors means changeable characteristics of the individual are not considered.
Structured Professional Judgement	Assessment of the presence and relevance of pre-defined factors, involving systematic evidence gathering and raters own knowledge and experience with the service user. Consideration of dynamic risk factors means ratings can be used to inform treatment efforts. Requires a higher level of training and time investment than unstructured and actuarial assessments.

1.3 Challenges of Assessing Shot-Term Risk of Inpatient Aggression

One of the key barriers to assessing service users' short-term risk of aggression is capturing episodic changes in risk state, but it is currently unclear to what extent dynamic risk factors fluctuate over short periods of time (Abidin et al., 2013a). Existing risk assessments measure a risk factor on one occasion and attempt to predict the occurrence of aggression in a subsequent time window, however, these discrete assessments cannot account for frequent variability in a risk factor (Coid et al., 2015). While existing risk assessments do offer some value in predicting aggression in the long-term, they are ill-suited to document how specific

risk factors vary over short time periods, and consequently how these changes are reflected in an individual's risk of short-term aggression. The amount of staff time required to complete these assessments makes more frequent assessments less feasible, therefore assessing short term change in dynamic risk factors requires an alternative method of capturing episodic change.

1.3.1 Experience Sampling Methodology

Experience Sampling Methodology (ESM) involves the repeated measurement of thoughts, feelings and behaviours during everyday life (Myin-Germeys et al., 2018). In early applications of this method questions were presented to participants through a booklet and pre-programmed wristwatch or personal digital assistant, but mobile phones have become increasingly popular (Myin-Germeys et al., 2009). A key benefit of ESM is in its ability to capture periodic changes in variables with minimal intrusion into individuals' daily activities.

Experience Sampling Methodology has been increasingly used as a research method, and a large body of research has demonstrated its feasibility and acceptability among individuals with schizophrenia-spectrum disorders. For example, multiple studies have illustrated that ESM can be used to acquire meaningful insight into positive symptoms (e.g. Ben-Zeev et al., 2011; Granholm et al., 2008) as well as mood (Kimhy et al., 2014). While ESM has been used to monitor fluctuations in self-harm behaviours and suicidal ideation in both inpatient and community settings (Husky et al., 2014; Kleiman et al., 2017), however this approach has not been used extensively to study inpatient aggression or in a forensic mental health setting. Humber et al. (2013) conducted one of the few ESM studies in a forensic setting, reporting that episodic changes in anger were significantly predictive of increased suicidal ideation among a UK prison sample. Experience Sampling Methodology is ideally suited to capture episodic change in dynamic risk factors and could illustrate how these risk factors vary over shorter time periods than is currently possible with existing risk assessments, and consequently whether these data are predictive of short-term aggression.

1.3.2 Passive Remote Monitoring of Psychophysiological Arousal

Another key barrier to the predictive accuracy of existing risk assessments is their inability to assess the psychophysiological arousal associated with aggression. Neurophysiological theories of aggression suggest that it is driven in part by autonomic nervous system dysregulation (Stahl, 2014), reflecting an imbalance between 'top-down' control processes and 'bottom-up' drives associated with structures of the limbic system (Siever, 2008) (see

Figure 1). This dysregulation can be inferred through changes in electrodermal activity and heart rate variability (HRV; Blake & Grafman, 2004), indices of sympathetic and parasympathetic nervous system activity.

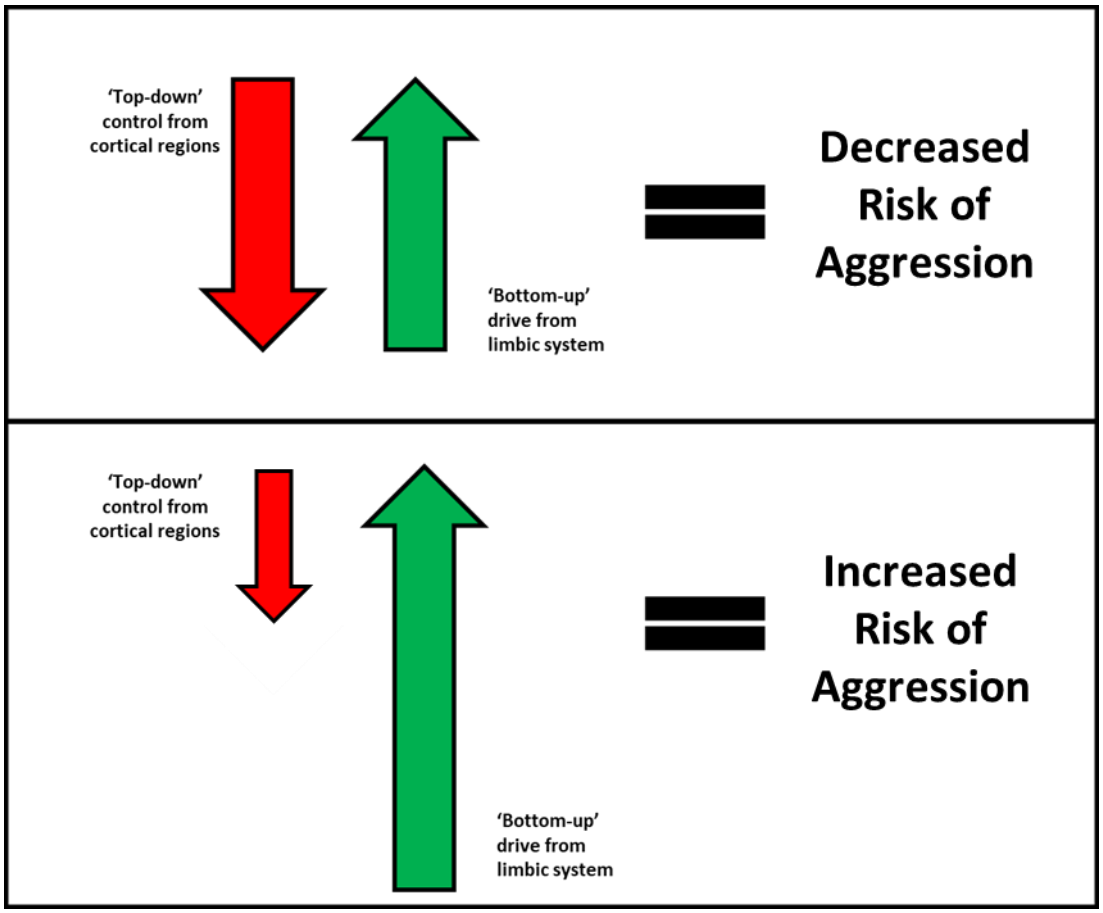

Figure 1 A balance between top-down and bottom-up drives resulting in behavioural inhibition and no aggression (top) versus an overly strong bottom-up drive and inhibited top-down control resulting in aggression (bottom) - adapted from Stahl (2014)

Previous research has reported an association between both psychophysiological hypoarousal and hyperarousal and aggression (Scarpa & Raine, 2000). Psychophysiological under-arousal is thought to underly predatory and planned forms of aggression and is typically reflected among individuals with DPD and psychopathic traits. For example, one dubiously ethical experimental technique is to induce stress among forensic mental health service users, and one study using this technique reported significantly diminished psychophysiological arousal among service users with DPD and psychopathic traits compared to other clinical groups and non-affected controls (Lobbestael et al., 2009). This pattern of hypoarousal is thought to reflect a diminished threat response (Herba et al., 2004; Kumari et al., 2009). Psychophysiological hyperarousal is believed to reflect reactive and impulsive forms of aggression (Scarpa et al., 2010), evidenced by elevated electrodermal activity (Armstrong et al., 2019; Murray-Close et al., 2017) and reduced HRV (Puhalla et al., 2019).

Previous research has been unable to capture changes in sympathetic and parasympathetic nervous activity in participants' everyday life, due to the costs and limited portability of the monitoring equipment. However, advances in passive remote monitoring (e.g. wearable sensors) now enables these parameters to be monitored continuously, with minimal intrusion in participants' daily activities.

There is developing interest in the role that passive remote monitoring technology could play in forensic mental health services (Gulati et al., 2016; Patel et al., 2018; Ramesh et al., 2018), though current evidence for its effectiveness in predicting inpatient aggression is still limited. Ben-Zeev et al. (2017) explored the association between physical activity data collected through a smartphone and violent ideation in a forensic mental health service and found that decreased physical activity was associated with a near 3-fold increase in violent ideation. To date, only one study has investigated using a wearable sensor in relation to inpatient aggression in a forensic mental health service (Looff et al., 2019). This study reported a significant elevation in heart rate and electrodermal activity 30-minutes prior to an aggressive incident. These findings tentatively suggest that, as with ESM, passive remote monitoring technology could provide a clearer understanding of how psychophysiological risk factors for inpatient aggression over short time periods and whether these short-term changes predict inpatient aggression.

1.4 Thesis Aims

This thesis investigates whether using ESM and passive remote monitoring in a forensic mental health service can identify short-term variability in dynamic risk factors and predict future aggression. This method could provide a clearer understanding of how dynamic risk factors for aggression vary over short time periods than is currently available through existing structured risk assessments. Identifying the time periods over which this association with aggression exists could also provide a window of opportunity to de-escalate aggressive situations and provide appropriate support to service users (see **Figure 2**).

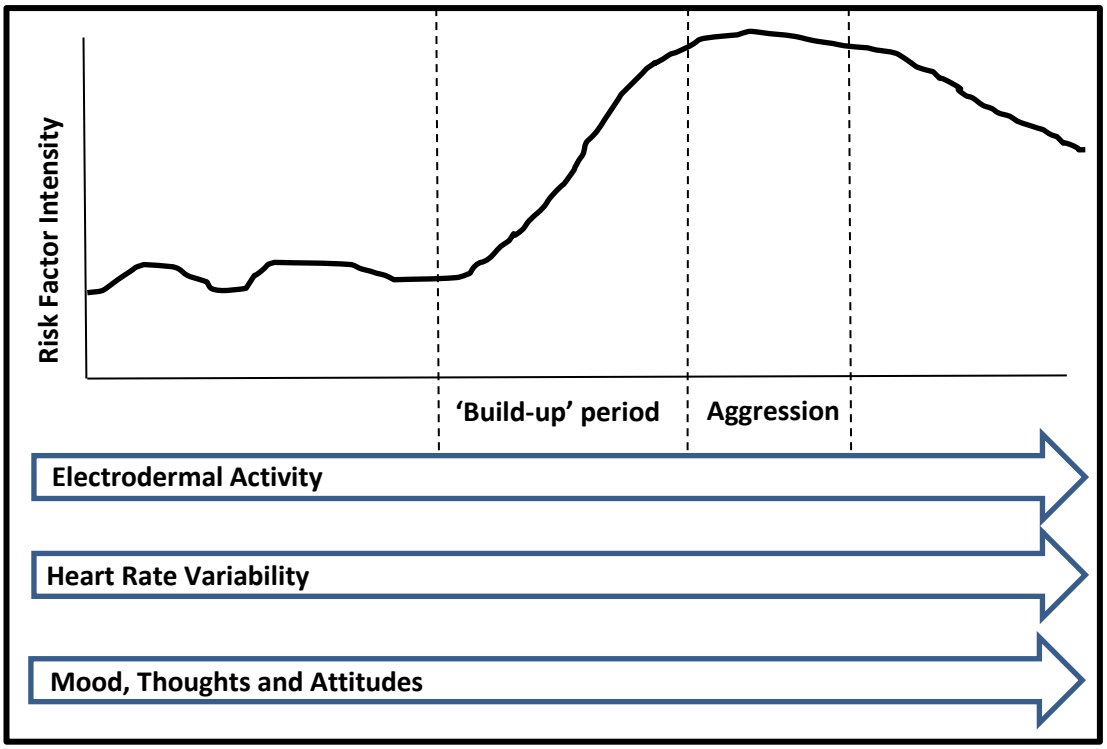

Figure 2 Theoretical illustration of short-term build-up in psychophysiological arousal and other dynamic risk factors for aggression

The overall thesis structure is:

Chapter 2: reports a systematic review of dynamic risk factors for inpatient aggression in mental health services to identify dynamic risk factors which show the most robust and reliable association with inpatient aggression for use in the ESM protocol.

Chapter 3: is a qualitative study of the perspectives of frontline staff in forensic mental health services towards passive remote monitoring for inpatient aggression to understand the potential benefits and implementation barriers to passive remote monitoring.

Chapter 4: reports a pilot study of ESM and passive remote monitoring among staff and service users in a forensic mental health service to evaluate the feasibility and acceptability of both ESM and passive remote monitoring.

Chapter 5: is a passive remote monitoring study of changes in staff psychophysiological arousal in relation to shift status to establish the optimum timeframe for identifying changes in psychophysiological arousal.

Chapter 6: is an ESM study of the variability in service users' dynamic risk factors to understand whether these factors predict future aggression.

Chapter 7: is a passive remote monitoring study of variability in service users' psychophysiological arousal to investigate how psychophysiological arousal can predicts future aggression over short time periods.

Chapter 8: combines the ESM and passive remote monitoring described in Chapters 6 and 7 to investigate whether the combined data improves the prediction of future aggression.

Chapter 9: presents an overall discussion of the key findings of the empirical chapters, this thesis contribution to existing literature and suggests areas for future research.

Chapter 2 : A Systematic Review of Dynamic Risk Factors for Inpatient Aggression in Mental Health Services

The work presented in this chapter has been published:

> Greer, B., Taylor, R.W., Cella, M., Stott, R., & Wykes, T. (2020). The contribution of dynamic risk factors in predicting aggression: A systematic review including inpatient forensic and non-forensic mental health services. *Aggression and Violent Behaviour, 53*. doi: 10.1016/j.avb.2020.101433

2.1 Introduction

Static risk factors such as past aggression (Van Dorn et al., 2017) are unchanging and offer little opportunity for short-term risk prediction. However, dynamic risk factors may be better suited to monitor changes in short-term risk state due to their closer temporal relationship with aggression (Klepfisz et al., 2016). For example, aggression is more likely when dynamic risk factors escalate, including increasing intensity of positive symptoms of psychosis (Coid et al., 2018; Keers et al., 2014) and reduced affect (Dean et al., 2007; Ullrich et al., 2014). Changes in dynamic risk factors may therefore indicate change in risk of aggression (Heffernan et al., 2019), though there is no evidence that they are causal (Ward, 2016).

In addition to identifying change in risk state, dynamic risk factors can represent specific areas of need where treatment should be focussed (Douglas & Skeem, 2005). They can therefore play an important role in reducing the likelihood of aggression and providing measurable outcomes for treatment progress (Andrews & Bonta, 2010). For example, two cluster randomised controlled trials reported significant reductions in the number of aggressive incidents among wards which conducted multiple, daily dynamic risk assessments, compared to wards which used infrequent clinical observations (Abderhalden et al., 2008; van de Sande et al., 2011). A suggested mechanism by which these reductions in aggression were achieved was an increased awareness of changes in participants' risk state, and staff support tailored towards higher-risk individuals.

Despite the large body of evidence investigating risk factors for aggression, it is unclear which dynamic risk factors are most relevant (i.e. predictive and replicable across samples). Previous research typically reports aggregate risk scores, meaning the predictive ability of individual risk factors is unclear. For example, some risk factors may significantly correlate with aggression due to a strong association with other risk factors, but may not have

independent predictive ability (Coid et al., 2011). Previous research also includes a range of assessment timeframes therefore the immediate antecedents of aggression are unclear.

The extent of overlap in risk factors between forensic and non-forensic inpatient mental health services is unknown. These services differ in relation to level of security and easier access to illegal drugs for example, an established risk factor for aggression (Van Dorn et al., 2017). Forensic mental health service users are also deemed to pose a greater risk of harm to others. A review by Witt et al. (2013) identified numerous dynamic risk factors associated with aggression, but did not differentiate between forensic and non-forensic services. This study also included data from community setting which differs substantially from inpatient settings and may entail different risk factors. This systematic review aims to synthesise the existing literature and examine the relationship between dynamic risk factors and inpatient aggression in inpatient mental health services, focussing on: i) the individual dynamic risk factors associated with inpatient aggression, ii) their temporal relationship with aggression, iii) their overlap with multiple forms of aggression, and iv) differences between forensic and non-forensic mental health services.

2.2 Method

2.2.1 Eligibility Criteria

Studies were eligible if they:

- Included adults (aged 18 or over) in a non-forensic or forensic inpatient mental health service, defined as any hospital-based service providing medical and psychological care for people with diagnosed mental health difficulties;
- Assessed factors reported by service users, staff, or risk assessment tools to be dynamic antecedents of aggressive incidents, or factors which immediately precede aggressive incidents;
- Reported aggressive behaviour occurring in inpatient services, including verbal and physical aggression towards others, aggression towards oneself (autoaggression), and aggression towards property;
- Were written in English.

Studies assessing the predictive validity of structured risk assessments were excluded, unless they provided results for dynamic risk factors specifically. This is because a large body of evidence exists regarding the predictive validity of risk assessment tools, but these are often reported at the scale level (Coid et al., 2011).

2.2.2 Search Strategy

This review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Moher et al., 2009). The protocol was registered on PROSPERO on 28th November 2017 (registration number: CRD42017082423). The final search was carried out on 21st November 2019 in Ovid MEDLINE(R), EMBASE, PsychINFO, CINAHL, and Web of Science from inception using the following search strategy:

- violen* OR aggressi*
- risk OR risk assessment OR predict* OR antecedent
- inpatient OR hospitali?ed OR mental OR psych* OR forensic OR secur*
- dynamic OR fluctuat* OR imminent

A grey literature search was undertaken through BASE, and reference lists of identified papers were searched for additional relevant studies. Two authors (BG and RT) independently screened studies by titles and abstracts and reviewed the full text to assess eligibility. Any inconsistencies were discussed until consensus was achieved. Data extraction for all identified studies was performed by BG, with RT independently extracting data from 25% of identified studies. Extracted data, consisting of the study country, participant demographics, study design and methodology, and aggressive outcomes, were cross-checked between both authors to ensure accuracy.

Where relevant information was not reported in the text, the authors were contacted to request this information. For quantitative studies, all risk factors were extracted irrespective of their significance to investigate whether the relevance of specific risk factors differed across samples. Where studies reported risk factors which appeared to refer to the same overarching domain, but whose terminology differed due to the measure used (e.g. 'mental state' and 'mental health'), these were grouped under one risk factor.

2.2.3 Study Quality

The quality of included studies was assessed using the Newcastle-Ottawa Scale for observational studies (Wells et al., 2011) which rates participant selection, comparability of cohorts, and outcome or exposure of interest. A maximum of four points can be awarded for participant selection, two for comparability, and three for outcome or exposure. The total score ranges from 0-9, with higher scores indicating higher methodological quality. Quality assessments were performed by BG, with RT independently rating quality for 25% of identified studies. Quality assessments were cross-checked between both authors to ensure accuracy.

2.3 Results

2.3.1 Study Selection

The initial search returned 3,588 studies, with 10 studies added through a grey literature search, and 16 after searching reference lists. After removing duplicates, 2,385 studies were screened and 25 met the inclusion criteria. **Figure 3** provides a breakdown of the screening process.

2.3.2 Study Characteristics

A total of 2,871 participants were included, and study sample sizes ranged from one to 370 (Mean = 111) with 17 studies including both men and women. Sixteen studies were conducted in forensic mental health services and nine in non-forensic mental health services, across nine countries: UK (*n* = 8), Netherlands (*n* = 5), USA (*n* = 4), Canada (*n* = 2), Sweden (*n* = 2), Australia (*n* = 1), Norway (*n* = 1), Germany (*n* = 1), and Ireland (*n* = 1). Additional study characteristics are presented in **Table 2**.

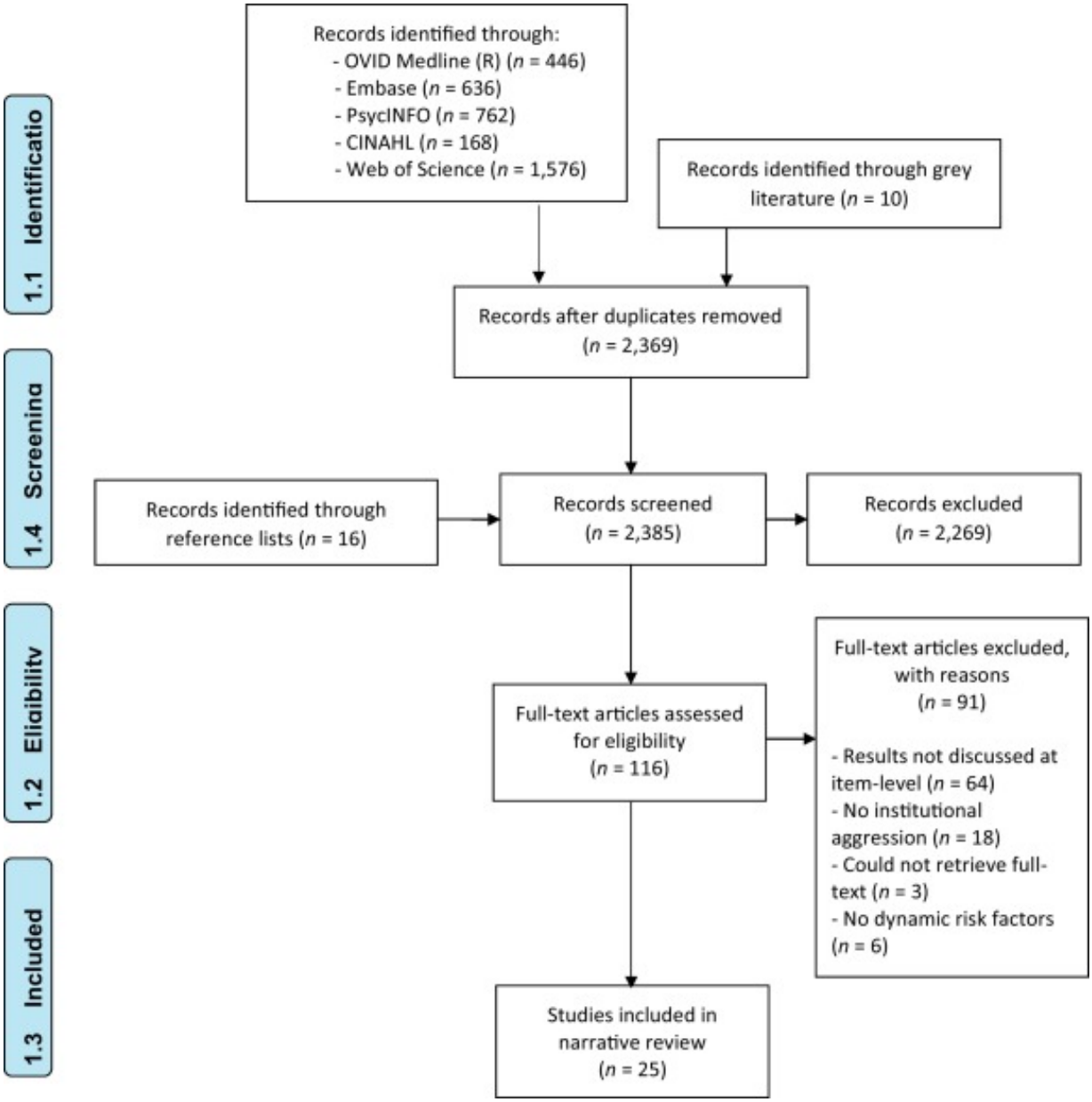

Figure 3 PRISMA flow diagram of study selection

Table 2 Study characteristics

Study	Country	Sample Characteristics	Clinical Characteristics	Method of Assessing Dynamic Risk Factors	Aggressive Outcome	Quality Assessment (0-9)
Forensic Mental Health Services (*n* = 16)						
Abidin et al. (2013)	Ireland	Men = 94 (94%) Women = 6 (6%) Mean Age = 40.45 SD = 12.8 Range = 21.1 - 69.3	Psychosis = 85 (85%) Affective Disorder = 12 (12%) Intellectual Disability = 3 (3%)	Structured Risk Assessment	Physical aggression towards others and autoaggression, assessed through routine incident reporting forms, daily nurse management logs, and statutory forms for seclusion and restraint	6
Brugman et al. (2016)	Netherlands	Men = 69 (100%) Mean Age = 37.9 SD = 7.9	Affective Disorder = 5 (7.2%) Personality Disorder = 69 (100%) Substance-use Disorders = 53 (76.8%) Developmental Disorder = 15 (21.7%) Other = 6 (8.7%) No Diagnosis = 10 (14.5%)	Emotional Stroop, Signal Detection Task, Graded Emotion Recognition Task	Physical and verbal aggression towards others, and property aggression, assessed using the Modified Overt Aggression Scale	6
de Looff et al. (2019)	Netherlands	Men = 68 (68%) Women = 32 (32%) Mean Age = 32.01 SD = 9.02 Range = 18-57	Intellectual Disability = 100 (100%)	Passive Remote Monitoring Device	Physical and verbal aggression towards others, autoaggression, and property aggression, assessed using the Modified Overt Aggression Scale+	8

Grevatt & Hughes (2004)	UK	Men = 44 (100%) Mean Age = 44 Range = 19-65	Psychosis = 24 (54.5%) Affective Disorder = 3 (6.8%) Personality Disorder = 11 (25%) Comorbid Psychosis/Personality Disorder = 6 (13.6%)	Structured Assessment	Risk	Physical and verbal aggression towards others, and property aggression, assessed using hospital incident reporting forms	6
Kelly et al. (2015)	USA	Men = 109 (31%) Women = 239 (69%) Age Not Specified	Not Applicable (Staff Members)	Staff Survey		Physical aggression towards others, assessed using an unvalidated Likert Scale	8
Linaker & Busch-Iversen (1995)	Norway	Men = 27 (84%) Women = 5 (16%) Age Not Specified	Not Specified	Structured Assessment	Risk	Physical aggression towards others, assessed using hospital records	7
Lindsay et al. (2004)	UK	Men = 5 (100%) Mean Age = 39.4 SD = 8.1 Range = 27-48	Intellectual Disability = 5 (100%)	Structured Assessment	Risk	Physical aggression towards others, assessed using hospital records	5

Mckenzie & Curr (2005)	UK	Men = 74 (79%) Women = 21 (21%) Mean Age = 35 Range = 18-62	Not Specified	Structured Assessment	Risk	Physical aggression towards others, assessed using hospital records	6
Meaden et al. (2013)	UK	<u>Service Users</u> Men = 18 (75%) Women = 6 (25%) Mean Age = 47 Range = 40-69 <u>Staff</u> Men = 13 (52%) Women = 12 (48%) Age Not Specified	<u>Service Users</u> Psychosis = 24 (100%)	Staff Interview		Physical aggression towards others, assessed using the Retrospective Overt Aggression Scale	5
Ogloff & Daffern (2006)	Australia	Men = 78 (78%) Women = 22 (22%) Mean Age = 32.95 SD = 11.83	Psychosis = 77 (77%) Affective Disorders = 11 (11%) Other = 12 (12%)	Structured Assessment	Risk	Physical aggression towards others, assessed using the Overt Aggression Scale	5
Selenius et al. (2016)	Sweden	Women = 130 (100%) Mean Age = 33 SD = 11.4 Range = 17-64	Psychosis = 32 (24.6%) Affective Disorder = 12 (9.2%) Personality Disorder = 77 (59.2%) Substance-use Disorder = 40 (30.8%) Developmental Disorder = 37 (28.5%)	Medical records		Physical and verbal aggression towards others, assessed using medical records, forensic psychiatric investigations and verdicts	5

Schuringa et al. (2018)	Netherlands	Men = 277 (100%) Mean Age = 36.7 SD = 9.6 Range = 20-68	Psychosis = 134 (48%) Affective Disorder = 33 (12%) Personality Disorder = 241 (87%) Substance-use Disorder = 218 (79%) Developmental Disorder = 69 (25%) Other = 77 (27.8%)	Structured Assessment	Risk	Physical aggression towards others, assessed using hospital records	5
Steptoe et al. (2008)	UK	Men = 23 (100%) Mean Age = 38.4 SD = 10.3	Intellectual Disability = 23 (100%)	Structured Assessment	Risk	Physical aggression towards others, assessed using hospital records	4
Tengström et al. (2006)	Germany	Men = 205 Women = 11 Mean Age = 38.05 SD = 10.16	Psychosis = 99 (45.8%) Personality Disorder = 66 (30.6%) Cognitive Impairment = 51 (23.6%)	Structured Assessment	Risk	Physical aggression towards others, assessed using hospital records and interviews with ward staff	5
Wang & Diamond (1999)	USA	Men = 331 (100%) Mean Age = 32.66 SD = 8.15	Psychosis = 139 (42%) Affective Disorder = 142 (43%) Personality Disorder = 228 (69%) Developmental Disorder = 26 (8%) Undiagnosed = 23 (7%)	Barratt Impulsiveness Scale, Buss-Perry Aggression Questionnaire, Personality Assessment Inventory		Physical and verbal aggression towards others, assessed using hospital records	4

Woods et al. (2015)	Canada	Men = 35 (76.1%) Women = 11 (23.9%) Mean Age = 35.85 SD = 13.34 Range = 17 - 66	Psychosis = 27 (58.7%) Affective Disorder = 6 (13%) Substance Use Disorder = 42 (91.3%) Dementia = 2 (4.3%) Other = 9 (19.6%) No Diagnosis = 3 (6.5%)	Structured Assessment	Risk	Physical and verbal aggression towards others, assessed using the Staff Observation Aggression Scale-Revised	6
Non-forensic Mental Health Services (*n* = 9)							
Bjorkdahl et al. (2006)	Sweden	Men = 37 (50.7%) Women = 36 (49.3%) Mean Age = 39.6	Psychosis = 39 (53.4%) Affective Disorder = 14 (19.1%) Personality Disorder = 9 (12.3%) Other Non-Psychotic Disorder = 11 (15.1%)	Structured Assessment	Risk	Physical aggression towards others, assessed using the Staff Observation Aggression Scale-Revised	5
Brewer et al. (2016)	UK	Men = 15 (51.7%) Women = 14 (48.3%) Men = 21-49 Women = 23-49	Psychosis = 7 (24.1%) Personality Disorder = 13 (44.8%) Intellectual Disability = 29 (100%) Autism Spectrum Disorder = 8 (27.6%)	Structured Assessment	Risk	Physical and verbal aggression towards others, autoaggression, and property aggression, assessed using the Modified Overt Aggression Scale, and Overt Aggression Scale-modified for neuro-rehabilitation	4

McDermott et al. (2008)	USA	Men = 91 (84%) Women = 17 (16%) Mean Age = 45.6	Psychosis = 78 (72.2%) Affective Disorder = 10 (9.3%) Personality Disorder = 34 (31.5%) Substance Use Disorder = 4 (3.7%) Other = 16 (14.8%)	Barratt Impulsiveness Scale, Brief Psychiatric Rating Scale Novaco Anger and Provocation Inventory	Physical aggression towards others, assessed using incident reporting forms	4
Reeves (2015)	Canada	Men = 101 (48%) Women = 107 (51%) Transgender = 1 (1%) Mean Age = 40.17 SD = 14.88 Range = 17-81	Psychosis = 83 (39.7%) Affective Disorder = 80 (38.3%) Personality Disorder = 8 (3.8%) Substance-use Disorder = 30 (14.4%) Other = 8 (3.8%)	Structured Risk Assessment	Physical and verbal aggression towards others, and property aggression, assessed using the Overt Aggression Scale and Staff Observation Aggression Scale-Revised	4
van de Sande et al. (2017)	Netherlands	Men = 52 (61%) Women = 33 (39%) Mean Age = 38	Psychosis = 47 (55%) Affective Disorder = 13(15%) Personality Disorder = 6 (7%) Substance Use Disorder = 11 (13%) Unknown = 7 (8%)	Validated observation scales	Seclusion following an aggressive incident, assessed using the Argus Scale	7
van de Sande et al. (2013)	Netherlands	Men = 187 (62%) Women = 114 (38%) Mean Age = 39 SD = 13	Psychosis = 144 (48%) Affective Disorder = 36 (12%) Personality Disorder = 39 (13%) Substance Use Disorder = 39 (13%) Unknown = 12 (4%)	Structured Risk Assessment	Seclusion following an aggressive incident, assessed using the Argus Scale	7
Werner et al. (1983)	USA	Men = 40 (100%) Age Not Specified	Psychosis = 29 (72.5%) Affective Disorder = 4 (10%) Other = 7 (17.5%)	Validated observation scales	Physical aggression, assessed using hospital records	6

Whittington et al. (2006)	UK	Men = 54% Women = 46% Age Not Specified	Not Specified	Incident Reporting Form	Physical restraint following an aggressive incident, assessed using incident reporting forms	5
Whittington & Patterson (1996)	UK	Men = 27 (43.5%) Women = 35 (56.5) Median Age = 47 Range = 19 - 85	Psychosis = 22 (35.5%) Affective Disorder = 9 (14.5%) Personality Disorder = 4 (6.5%) Organic Brain Syndrome = 8 (12.9%) No Diagnosis = 15 (24.2%)	Incident Reporting Form	Physical aggression towards others, assessed using incident reporting forms	3

2.3.3 Quality Assessment

No studies obtained the maximum score of nine on the Newcastle-Ottawa Scale, with studies scoring 8 (n=2), 7 (*n*=3), 6 (*n*=6), 5 (*n*=8), 4 (*n*=5), and 3 (*n*=1). The most common quality problems included inadequate follow-up periods, lack of detailed information about participant selection, and failing to control for confounding variables. Sixty-seven percent of studies in non-forensic services and 50% in forensic services obtained a quality score of five or below.

2.3.4 Outcome Measures

Incident reporting forms and nurse management logs were used by 13 studies. Validated informant report tools were used by 10 studies, with two studies using an informant report tool created by the authors of the study. Three studies (van de Sande et al., 2017; van de Sande et al., 2013; Whittington et al., 2006) used a seclusion measure, a proxy for aggression in this review. This management strategy is specifically employed to manage aggressive and disruptive behaviour, and its inclusion is consistent with previous research (Miller et al., 2013; Sedgwick et al., 2016). However, a limitation of this approach is that it is unable to distinguish between specific forms of aggression. The number of aggressive incidents reported ranged from 7 (Abidin et al., 2013) to 444 (van de Sande et al., 2017), and two studies did not report the frequency of aggression (Brewer et al., 2016; Steptoe et al., 2008).

2.3.5 Dynamic Risk Factors in Forensic Services

Sixty-one risk factors were identified from studies in forensic mental health services. **Figure 4** illustrates the number of studies reporting statistically significant relationships with inpatient aggression, out of the total number of studies examining this risk factor. Some risk factors are reported as outcome or predictors in different studies, due to different research questions. For example, six studies included verbal aggression as an outcome, but other studies (e.g. Bjorkdahl et al., 2006) reported this as a risk factor, because their outcomes were physical aggression. Various methods were used to investigate the association between risk factors and aggression, including qualitative reports from staff, receiver operating characteristic curves, hazard ratios, linear regression, and bivariate correlations, and were therefore subjected to narrative review. For the 15 quantitative studies, risk factors which reported both significant and non-significant associations with aggression were extracted (see Appendix 1).

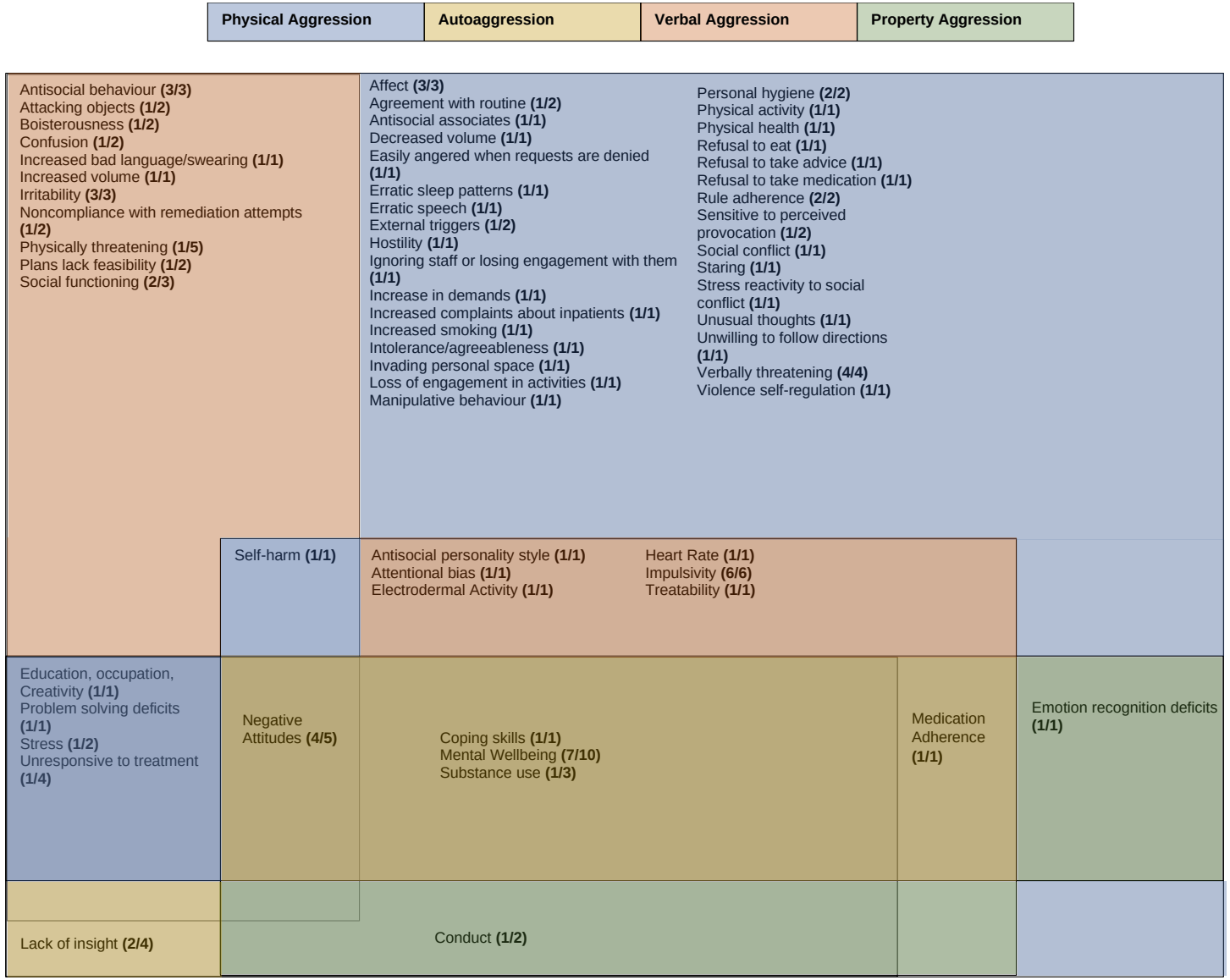

Figure 4 Dynamic risk factors for inpatient aggression in forensic mental health

2.3.6 Physical Aggression Towards Others

Sixteen studies reported 32 dynamic risk factors for physical aggression towards others. Brugman et al. (2016) reported a significant negative association between ***impulsivity*** and physical aggression, assessed through an affective Go/No Go task. These results are consistent with inhibitory control deficits reported as characteristic of individuals with mental health difficulties and a history of violence (Barkataki et al., 2008; Lievaart et al., 2018; Zhang et al., 2017).

de Looff et al. (2019) was the only study to investigate psychophysiological correlates of aggression, using a passive remote device (i.e. wearable wristband) continuously measuring changes in ***electrodermal activity*** and ***heart rate***, indices of autonomic nervous system activity. This study found a significant increase in both electrodermal activity and heart rate, compared to the participants' baseline, 30-minutes prior to an aggressive incident. To our knowledge this study is the first to use wearable remote monitoring technology to study inpatient aggression.

Twelve studies used validated assessment tools and were typically rated as higher quality for this criterion than those using non-validated methods (e.g. staff interviews). For example, the interviews employed by Meaden et al. (2013) enabled idiosyncratic risk factors to be identified, but also produced contradictory findings (e.g. ***decreased volume*** and ***increased volume*** were both associated with aggression). Identified risk factors were also often reported among individuals who did not commit an act of aggression, indicating a lack of specificity.

Discrepant results were reported by Selenius et al. (2016) who reported that ***self-harm*** was significantly associated with physical aggression towards staff, but not towards other service users. One possibility for these differences is the tendency for staff-directed aggression to occur in response to staff-imposed restrictions or requests, and therefore driven primarily by anger and emotional dysregulation (Quanbeck et al., 2007). No other studies differentiated between the different victims of aggression in their analyses, therefore it is unclear whether identified risk factors are specific to a victim group.

2.3.7 Verbal Aggression

Six studies reported 11 dynamic risk factors for verbal aggression, all of which were also associated with other forms of aggression. Verbal aggression was significantly associated with having an attentional bias towards general threat and aggression, in addition to emotion

recognition deficits for sad and happy faces (Brugman et al., 2016). These findings are consistent with models of aggression in mental health populations and previous experimental literature, implicating deficits in facial affect recognition (Malone et al., 2012) and hostile attribution bias (Harris, Oakley, & Picchioni, 2014) in aggressive behaviour. Impulsivity produced heterogenous findings, as it was weakly, but significantly, associated with verbal aggression (Wang & Diamond, 1999), but not found to be statistically significant in other studies (Brugman et al., 2016; Grevatt et al., 2004). These differences could reflect general difficulties in assessing impulsivity, as structured risk assessments often do not differentiate between trait (static) and state (dynamic) impulsivity (Nguyen et al., 2018). As with physical aggression, Selenius et al. (2016) reported that self-harm was significantly associated with verbal aggression towards staff, but not towards other service users, but was the only study to differentiate between victims of verbal aggression in their analysis.

2.3.8 Autoaggression

Only one study investigated dynamic risk factors for autoaggression (i.e. self-harm) and identified nine risk factors (Abidin et al., 2013). Five structured risk assessment tools were used, but there was little replicability in the risk factors identified. For example, while three assessment tools identified statistically significant risk factors associated with service users' current ***mental wellbeing***, this was not found in a fourth assessment tool. Two tools assessed ***holding negative attitudes,*** with only one finding it statistically significant. One explanation for these findings may be the low rate for autoaggression (3.8 per 10,000 patient-days at risk), which may be insufficient for the identification of statistically significant effects. The assessment tools were also rated by different staff so rating discrepancies may also account for the different results.

2.3.9 Property Aggression

Three studies reported five dynamic risk factors for property aggression, all of which were also associated with other forms of aggression. Risk factors corresponded to heightened psychophysiological arousal (***electrodermal activity*** and ***heart rate***; de Looff et al., 2019), cognitive difficulties including ***lack of insight, mental wellbeing*** (Grevatt et al., 2004) and ***emotion recognition deficits*** (Brugman et al., 2016). Grevatt et al., (2004) included multiple forms of aggression, but did not report which risk factors were associated with property aggression specifically. Rates of property aggression were also lower in these studies compared to other forms of aggression (36% and 0.7%, respectively) or not reported at all (Brugman et al., 2016). As with autoaggression, because of the increased risk of false

positives with a low base rate, it is possible that reported associations reflect this low incidence.

2.3.10 Overlap with Non-Forensic Services

Figure 5 illustrates the additional risk factors identified in studies in non-forensic services, and the overlap with forensic services. Thirteen dynamic risk factors, not otherwise identified in studies in forensic services, were reported in six studies in non-forensic services (Brewer et al., 2016; Reeves, 2015; van de Sande et al., 2017; Werner et al., 1983; Whittington et al., 2006; Whittington & Patterson, 1996). These factors were only assessed by studies in non-forensic services and were typically low-quality studies. Only two studies obtained a score over five on the Newcastle-Ottawa Scale (van de Sande et al., 2017; Werner et al., 1983).

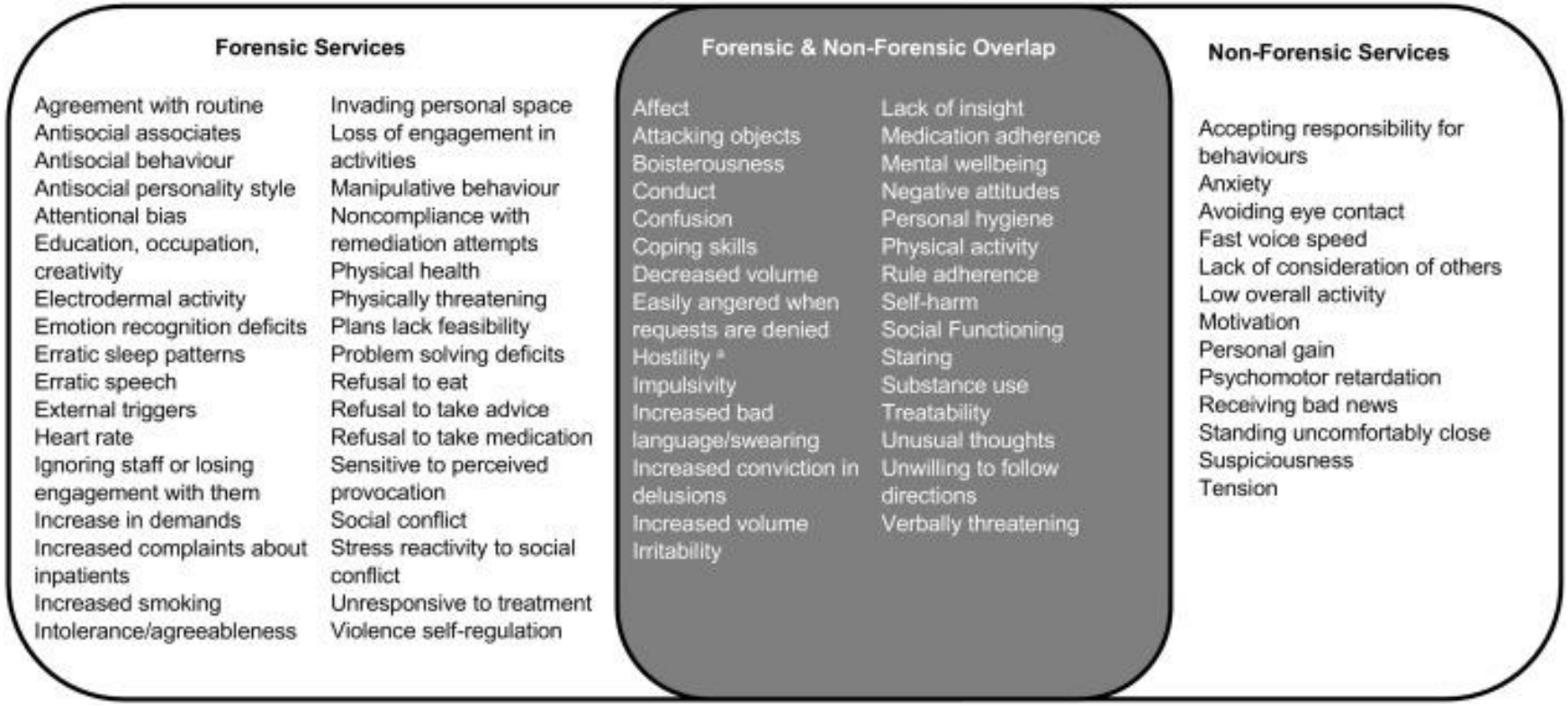

Figure 5 Overlap of risk factors between forensic and non-forensic services

2.3.11 Non-Significant Risk Factors

Twenty risk factors were not reported as statistically significant by any study which assessed them (see **Table 3**). As with the factors previously discussed, these non-significant factors related to cognitive/affective (e.g. ***hopelessness***, ***suicidal ideation, and sexual preoccupation***) and behavioural (e.g. ***mannerisms and posturing*** and ***sexual self-regulation****)* characteristics of the individual. Factors related to perceived future (e.g. ***future service contact*** and ***future response to psychological intervention***) were also assessed. Fifteen were only assessed by one study, and five were assessed by two studies using the same measure. Of the seven studies reporting these non-significant risk factors, five scored over five on the Newcastle-Ottawa Scale.

Table 3 Non-significant risk factors

Study	Risk Factor
Abidin et al. (2013)	Material resources Suicidal ideation Hopelessness Future service contact Future response to drug treatment Future response to psychological intervention Leave
Brugman et al. (2016)	Vigilance for threatening stimuli Implicit associations with violence Emotion recognition deficits (anxiety, surprise, disgust)
Grevatt & Hughes (2004)	Violent lifestyle
Schuringa et al. (2018)	Sexually deviant behaviour
Steptoe et al. (2008)	Sexual self-regulation
van de Sande et al. (2017)	Mannerisms and posturing Grandiosity Uncooperativeness Distractibility Sexual preoccupation Helplessness
Werner et al. (1983)	Mannerisms and posturing Grandiosity Uncooperativeness

2.3.12 Relevance for Targeted Monitoring and Support

The temporal relationship between risk factors and aggressive outcome determines whether there is enough time for preventative support or emergency actions such as restraint and seclusion. However, a longer time period between the risk factor and aggression may mean additional risk factors arise during this time.

As shown in **Figure 6**, follow-up periods ranged up to 30 months, so some identified risk factors may have limited usefulness for preventative support. For example, Bjorkdahl et al. (2006) and Linaker and Busch-Iversen (1995), both investigated physical aggression over a 24-hour period, and reported several factors as statistically significant, including ***irritability***, ***boisterousness***, and ***verbal threats***. These factors were not statistically significant in van de Sande et al. (2013), which had a considerably longer follow-up period of 12-months and used the same structured risk assessment. This may be because the impact of these risk factors diminished over time, meaning targeted support may no longer be useful for this risk factor. de Looff et al's. (2019) real-time assessment of psychophysiological arousal represents a novel approach to monitoring risk factors for aggression. This approach could provide greater temporal accuracy than with traditional structured risk assessment instruments, by identifying changes in risk factors as they occur.

Identifying risk factors which may be most useful for targeted monitoring and treatment also depends in part on their replicability across samples. Twenty-six risk factors had a statistically significant relationship with aggression reported in two or more studies (see **Table 4**). The low number of high-quality studies suggests that even these risk factors should be interpreted with caution in the absence of replication in higher quality studies.

Most studies did not report the amount of missing data in their assessments, which could mask changes in the risk factor over time, and subsequently whether targeted support is required. For example, Woods et al. (2015) conducted risk assessments frequently (two per day for each participant over 12 weeks), but reported that 18% of their data was missing and could not be included in their

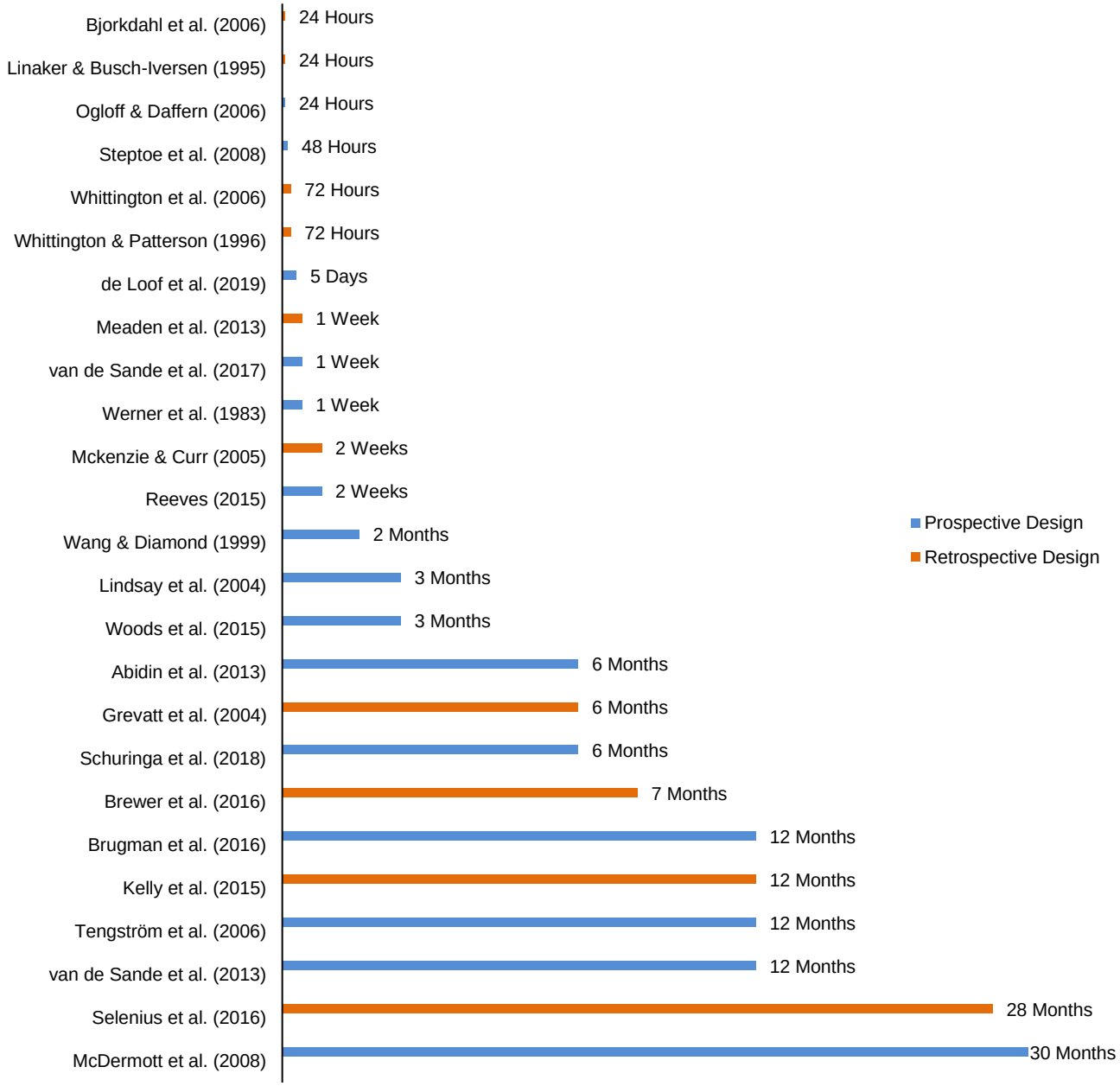

Figure 6 Follow-up period of studies included in this systematic review

Table 4 Dynamic risk factors reported significant by at least two studies

Risk Factor	Studies	Physical Aggression	Verbal Aggression	Autoaggression	Property Aggression	Seclusion/Restraint
Affect	Abidin et al. (2013)	+				
	Brewer et al. (2016)				+	
	Lindsay et al. (2004)	/				
	Steptoe et al. (2008)	+				
	van de Sande et al. (2017)					+
	Werner et al. (1983)	-				
Antisocial Behaviour	Lindsay et al. (2004)	/				
	Schuringa et al. (2018)	/				
	Steptoe et al. (2008)	+				
Anxiety	Brewer et al. (2016)	+	+	+	+	
	van de Sande et al. (2017)					+
	Wang & Diamond, (1999)	+	+			
Attacking Objects	Linaker & Busch-Iversen, (1995)	+				
	Whittington & Patterson, (1996)	Q				
Boisterousness	Björkdahl et al. (2006)	+				
	Linaker & Busch-Iversen, (1995)	+				
Conduct	Abidin et al. (2013)	+				
	Brewer et al. (2016)		+		+	
Confusion	Björkdahl et al. (2006)	+				
	Linaker & Busch-Iversen, (1995)	+				
	van de Sande et al. (2013)					+
	Whittington & Patterson, (1996)	Q				

Coping Skills	Abidin et al. (2013)	+				
	Brewer et al. (2016)	+	+	+	+	
Easily Angered when Requests are Denied	Ogloff & Daffern, (2006)	+				
	Reeves, (2015)	+				
Hostility	McDermott et al. (2008)	+				
	Reeves, (2015)	+				
	Schuringa et al. (2018)	/				
Impulsivity	Abidin et al. (2013)	+				
	McKenzie & Curr (2005)	+				
	Ogloff & Daffern, (2006)	+				
	Schuringa et al. (2018)	/				
	Tengström et al. (2006)	+				
	Wang & Diamond, (1999)		-			
Increased Bad Language/Swearing	Meaden et al. (2013)	Q				
	Whittington & Patterson, (1996)	Q				
Increased Volume	Meaden et al. (2013)	Q				
	Whittington et al. (2006)					+
	Whittington & Patterson, (1996)	Q				
Irritability	Björkdahl et al. (2006)	+				
	Linaker & Busch-Iversen, (1995)	+				
	Woods et al. (2015)	+				
Lack of Insight	Brewer et al. (2016)	+	+	+		
	Grevatt et al. (2004)	+				
	Tengström et al. (2006)	+				

Mental Wellbeing	Abidin et al. (2013)	+		+		
	Brewer et al. (2016)	-	-		-	
	Grevatt et al. (2004)	+				
	McDermott et al. (2008)	+				
	Meaden et al. (2013)	Q				
	Werner et al. (1983)	+				
	Whittington & Patterson (1996)	Q				
Negative Attitudes	Abidin et al. (2013)	+		+		
	Brewer et al. (2016)	-	-	-	-	
	McKenzie & Curr (2005)	+				
	Ogloff & Daffern, (2006)	+				
	Reeves, (2015)	+				
	Tengström et al. (2006)	+				
Personal Hygiene	Abidin et al. (2013)	+				
	Brewer et al. (2016)	+	+	+	+	
Quiet	Meaden et al. (2013)	Q				
	Whittington & Patterson, (1996)	Q				
Rule Adherence	Abidin et al. (2013)	+				
	Brewer et al. (2016)	-				
	Schuringa et al. (2018)	/				
Self-Harm	Selenius et al. (2016)	+	+			
	Whittington et al. (2006)					+
Social Functioning	Abidin et al. (2013)	+				
	Meaden et al. (2013)	Q				

Substance Use	Abidin et al. (2013)	+			
	Brewer et al. (2016)	-	-	-	-
Treatability	Abidin et al. (2013)	+			
	Brewer et al. (2016)		-		
Unwilling to Follow Directions	Ogloff & Daffern, (2006)	+			
	Reeves, (2015)	+			
Verbally Threatening	Björkdahl et al. (2006)	+			
	Linaker & Busch-Iversen, (1995)	+			
	Reeves, (2015)	+			
	Whittington & Patterson, (1996)	Q			
	Woods et al. (2015)	+			

+ statistically significant positive association with aggression, - statistically significant negative association with aggression, / statistically significant differences between aggressive and non-aggressive participants, Q qualitative reports from staff of relevant/observed risk factors

predictive analysis. For studies using infrequent assessments which have a limited amount of data, avoiding missing data is a particularly important issue for ensuring accurate analyses can be conducted.

Nine studies may suffer from recall and subjective interpretation bias as they required staff members to report which risk factors, they believed an individual was presenting prior to an aggressive incident. Risk factors and their severity may be missed or incorrectly recorded during recall, as suggested in a previous review of inpatient aggression where no clear cause was attributed to approximately one third of all of aggressive incidents (Papadopoulos et al. 2012).

2.4 Discussion

2.4.1 Overlapping Risk Factors

This review builds on previous studies of dynamic risk factors and aggression (e.g. Witt et al. 2013), by exploring differences between types of inpatient services, and overlap among multiple forms of aggression. There is a lack of evidence that dynamic risk factors differ between forensic and non-forensic services. While 18% of risk factors were only reported in non-forensic mental health services, there is no theoretical explanation why risk factors, such as ***anxiety*** or ***receiving bad news,*** would only be relevant to non-forensic mental health service users. It is likely that these factors were absent because they were not assessed. This has practical implications for managing risk of aggression in mental health services, as it suggests that risk factors are not specific to different mental health services. The 20 non-significant risk factors identified in this review may have limited predictive ability for inpatient aggression, particularly those reported in high-quality studies. However, the small number of studies assessing these factors suggests future research is warranted before concluding that these factors have no clinical utility.

Physical violence is most often measured in previous research, but by including verbal, property and autoaggression as outcomes, this systematic review identified that 94% of dynamic risk factors were associated with more than one type of aggression. This suggests that individual risk factors may indicate the likelihood of multiple aggressive outcomes, but study methodology is also likely to account for much of this overlap. For example, multiple studies assessed the same risk factors meaning it is unsurprising that overlap was identified. High levels of intercorrelation across risk factors and structured risk assessments, as reported in previous studies (Arbach-Lucioni et al., 2011; Desmarais et al., 2012), could also explain this overlap.

2.4.2 Sources of Data

There is a paucity of information from the perspective of service users regarding what factors they believe contribute to aggression, and there are likely differences between service users and staff in this respect. For example, service users have cited environmental conditions and poor communication with staff as a salient cause of inpatient aggression, while staff often referred to service users' mental state (Duxbury & Whittington, 2005). Future research could therefore explore whether service users themselves regard risk factors reported by staff as relevant, which may provide a more nuanced understanding of personally relevant risk factors. An improved understanding of what service users deem to be the important causes of their aggressive behaviour would also be consistent with clinical guidelines, which stipulate the need to involve service users in the development of their risk management plans (National Institute for Health and Care Excellence, 2015).

Thirteen studies used hospital records and incident logs as the sole outcome measure for aggression. The reporting accuracy of staff, and their perceived threshold for when behaviour constitutes aggression, will therefore determine the accuracy of these measures (Iozzino et al., 2015). In settings with a high base rate of aggressive incidents, or where a large proportion of incidents are accounted for by a small proportion of service users, staff may be more likely to report severe outcomes, and under-report those that are less severe (e.g. verbal aggression and physical assaults not resulting in injury).

2.4.3 Study Quality and Methodology

Methodological limitations meant there were few high-quality studies included, highlighting the need for future research which addresses these limitations. Many studies used follow-up periods over several months, with the longest follow-up being two years from the assessment of the dynamic risk factors. The length of time between assessment and outcome in these studies means the assessed risk factors may no longer be relevant when the aggressive outcome eventually occurred. For example, participants who were rated as impulsive by Schuringa et al. (2018) at the time of assessment could have more or less impulsivity six months later when aggressive outcomes were recorded. Such factors may be of limited usefulness for efforts to predict aggression in the short-term. There is therefore a need for future research with greater temporal resolution (i.e. frequent assessments conducted close-in-time to aggressive outcomes).

The number of risk factors assessed in each study ranged from two (de Looff et al., 2019) to 40 (Abidin et al., 2013). Few studies corrected for multiple comparisons, therefore increasing

the risk of false positives (further exacerbated by the risk of publication bias in the literature (Singh et al., 2013). This is an important issue for studies investigating inpatient aggression and other outcomes with low base-rates (e.g. suicide), where a greater number of individuals will be identified as being at risk (Ogloff & Daffern, 2006). Future research should therefore minimise the risk of family-wise error, such as employing Bonferroni corrections as used by Lindsay et al. (2004), or adjusting alpha levels *a priori* to correct for multiple comparisons, as was the case in Selenius et al. (2016). Studies which use multiple assessments, where repeated measurements may create nested-hierarchies of data, should also use statistical procedures which can account for the hierarchical nature of this data, such as multilevel modelling as used in van de Sande et al. (2013; 2017).

Only two studies included raters who were blind to the aggressive outcomes (Grevatt et al., 2004; Tengström et al., 2006). Risk ratings in the remaining studies may therefore have been biased by staff members' knowledge of whether the individual had committed an act of aggression, particularly in those studies where the victims of the incidents were also the raters (e.g. Whittington & Patterson, 1996). To minimise the risk of rater-bias, future research should ensure that raters who are evaluating risk factors do not know the number and severity of an individual's aggressive incidents.

2.4.4 Future Directions

Methodological limitations (i.e. infrequent assessments and long follow-up periods) mean the temporal relationship between risk factors and aggression in many studies is unclear. Consequently, the usefulness of risk factors identified for targeted monitoring and treatment warrants further investigation using prospective assessments close-in-time to the aggressive outcome. Clarifying the timeframe linking risk factors to aggressive outcomes could improve risk management and de-escalation protocols. This may also allow staff to concentrate resources to address risk factors that are manageable within realistic response timeframes, for example, or whether more immediate interventions are necessary. The relationship between risk factors and severity of harm caused by an aggressive incident is also unclear, as most studies did not report or assess this information. By recording both the frequency and severity of aggressive outcomes, future research could clarify the risk factors associated with more severe outcomes. This could inform risk management approaches by prioritising those risk factors associated with the most severe outcomes.

Many identified risk factors relate to subjective emotional states (e.g. ***anxiety*** and ***stress***) and attitudes which can be monitored frequently in near real-time through remote

monitoring technologies, such as electronic diaries and wearable devices to capture psychophysiological changes (Myin-Germeys et al., 2009). Evidence for a potential relationship between psychophysiological arousal and distressing symptoms can be seen in Cella et al. (2019) and de Looff et al. (2019), and represents a potential avenue for future research, so real-time changes in dynamic risk factors could be identified, and their subsequent impact on aggression investigated. In addition to circumventing limitations associated with infrequent assessments, this approach has an advantage over current structured risk assessments, which are relatively inflexible in their application, as they can be tailored towards those risk factors which are relevant for the individual.

2.4.5 Limitations

Dynamic risk factors may not have a direct causal relationship with aggression, but instead be mediated or moderated by additional factors, for example, state anger (Ullrich et al., 2018). Two studies reported the influence of additional factors, but mediating/moderating variables were not included in our search strategy, meaning these studies may not have been returned. Of the two studies included in this review, Kelly et al. (2015) reported that stress reactivity to social conflict (considered to be a relatively static but at times a dynamic variable; Schlotz, Yim, Zoccola, Jansen, & Schulz, 2011) was a significant moderator of the relationship between staff-staff conflict and aggression, suggesting it was the individual response to stress, not simply the presence of inter-staff conflict, that was associated with an increased risk of aggression. van de Sande al. (2017) reported that combining static (e.g. ethnicity) and dynamic (e.g. suspiciousness and negativism) factors into their regression models increased the likelihood of seclusion by an average of over four percentage points to 9.1%. To our knowledge there has been no systematic investigation of mediating/moderating variables in the relationship between dynamic risk factors and aggression, representing an opportunity for future research. While static risk factors may not share a close temporal relationship with aggressive outcomes, they should be considered in analyses and support provided by staff together with dynamic risk factors to better understand this complex relationship.

As the focus of this review was individual risk factors, the search strategy adopted excluded studies reporting aggregate risk factors (e.g. McDermott et al., 2011; Vitacco et al., 2009). Future reviews may consider how best to incorporate results reported at the individual and scale-level. Aggression has no consistent definition which complicates comparisons between studies (Harris et al., 2013). This review distinguished between different aggressive

outcomes, but the form of aggression reported by as many as 13 studies is unclear. To aid comparisons between studies future research should ensure that the precise nature of the aggressive outcome is reported clearly.

2.5 Chapter Conclusion

This systematic review identified that while a large range of dynamic risk factors for inpatient aggression have been reported, a substantially smaller number demonstrate good levels of replicability and predictive ability. These risk factors were selected as candidates for the ESM and passive remote monitoring procedures used in later studies in this thesis, with Chapter 6 outlining the process by which the final set of dynamic risk factors was chosen. This review also highlighted multiple limitations of previous research which this thesis will address. For example, studies in this review typically used infrequent assessments of risk factors which were separated by days, weeks or months. These studies could therefore not investigate to what extent these risk factors vary over shorter periods of time and how these short-term changes relate to risk of future aggression. Chapter 5 outlines the process which assessed the optimal timeframes for identifying significant change in these risk factors, with Chapters 6, 7 and 8 investigating the magnitude of change over these timeframes and the relationship to aggression. Another key limitation of studies in this review was a lack of raters who were blind to the aggressive outcomes, raising the possibility that their risk ratings were influenced by the knowledge of service users' aggressive behaviour. The remote monitoring methods used in this thesis overcame this limitation as risk factor ratings were separate from staff members' recording of aggressive incidents.

Chapter 3 Predicting Inpatient Aggression in Forensic Services Using Remote Monitoring Technology: Qualitative Study of Staff Perspectives

The work presented in this chapter has been published:

> Greer, B., Newbery, K., Cella, M., & Wykes, T. (2019). Predicting inpatient aggression in forensic services using remote monitoring technology: qualitative study of staff perspectives. *Journal of medical internet research*, *21*(9), e15620.

3.1 Introduction

The Introduction to this thesis highlighted the role that ESM and passive remote monitoring technology could play in forensic mental health services, and a user-centred design approach to digital health technology, involving co-development with end-users, is central to achieving acceptable monitoring procedures and meaningful clinical benefits (Biagianti et al., 2017). Using digital technology to monitor risk of aggression would involve significant input from staff, to monitor device use, provide immediate support to users in the event of technical difficulties, interpret the data, and decide on an appropriate response (if any). Frontline staff would therefore play an integral role but, to our knowledge, their views around using this technology for monitoring risk of aggression have not been formally investigated.

Previous research on staff views of digital technologies in mental health identified issues which may be relevant when considering their role in monitoring risk of aggression. One issue identified concerns the digital literacy barriers that may exist among users, an issue which is known to disproportionately affect people with mental health difficulties (Greer et al., 2019). Among staff in early intervention for psychosis services, Bucci et al. (2019) reported that lack of familiarity and experience with digital technology was considered a barrier to using digital health technology (in this case a smartphone application to support self-management for people with psychosis). This did not just concern service users' ability to engage with the technology, but also reflected staff members' perceived lack of familiarity and confidence in using this technology. In general, staff believed digital health technology was more suited to younger generations of staff and service users. Similarly, Berry et al. (2017) reported a perceived barrier to service user engagement with digital health technology due to a digital divide. Participants in that study were employed in secondary care services, a rehabilitation service, and a community mental health team, suggesting this concern is wide-ranging and does not relate to service users in a specific setting.

The accuracy of the information collected through digital health technology has also been questioned by staff, particularly the proportion of false-positive and false-negative predictions. This issue was raised in Goodwin et al. (2019), which investigated whether passive remote monitoring technology could predict aggression among youths diagnosed with Autism Spectrum Disorder. The views of clinical staff in that study were not formally investigated, but staff did provide anecdotal feedback regarding the potential harm that may be associated with either a false-positive or false-negative prediction. Despite this, staff suggested that false positives might be tolerated by the potential to avoid or reduce the severity of an aggressive incident.

Staff were also concerned about the negative impact on users associated with digital health technology. Bourla et al. (2018) surveyed psychiatrists' attitudes towards three proposed digital health systems, including active and passive remote monitoring technology, and reported a range of concerns. In addition to false-positives and false-negatives reported by Goodwin et al. (2019), staff raised medico-legal concerns around providing treatment based on the outcome of a digital algorithm. Passive remote monitoring specifically was associated with several areas of concern, including the suggestion that continuous monitoring might exacerbate symptoms of anxiety, and could be stigmatising due to its perceived similarity to wearable GPS tracking of offenders. Of all three proposed digital health systems, participants rated the passive remote monitoring device as the least acceptable. Both Bourla et al. (2018) and Bucci et al. (2019) also identified concerns around the impact of digital health technology on the role of staff, highlighting the clinical value of face-to-face care which may not be achieved through remote digital technology. For this reason, staff believed that technology should complement rather than replace conventional care.

While studies of staff have highlighted areas of concern, potential benefits have also been reported. For instance, staff in Bucci et al. (2019) highlighted that digital healthcare technology had the potential to provide service users with on-demand support regardless of time or their location, enable users to take a more active role in managing their mental health, and represents a contemporary approach to healthcare which reflects the ubiquity of technology in modern life. Similar potential benefits were identified by Berry et al. (2017), in addition to enabling users with memory difficulties to record relevant health data in-the-moment. Seeking the views of staff can therefore provide an informative picture of both the challenges associated with introducing digital health technology, and the benefits associated with its introduction.

Adoption and adherence rates of novel digital health technology are poor (Greenhalgh et al., 2017), and frontline staff have reported that they do not receive adequate training or consultation about its introduction (Breedvelt et al., 2019; Royal College of Nursing, 2011, 2013). In addition, forensic mental health services may feature unique characteristics and barriers to digital technology not reflected in previous research (e.g. restricted internet connectivity, prohibited use of certain electronic devices etc…). To ensure any technology which is introduced is relevant and acceptable in clinical practice, it is essential to understand the views of staff towards monitoring the risk of aggression and the barriers that may be faced. Therefore, the aim of this study was to explore the views of staff toward passive remote monitoring technology for risk of aggression in inpatient forensic mental health services, with a focus on the potential benefits that this technology could provide and barriers to implementation.

3.2 Method

3.2.1 Design

This was an exploratory qualitative study using focus groups following a topic guide. Ethical approval was obtained from the Yorkshire & The Humber-Bradford Leeds Proportionate Review Service (18/YH/0221) and King's College London Psychiatry, Nursing and Midwifery Research Ethics Panel, London, UK (LRS-17/18-6715).

3.2.2 Participants

Participants were staff in a medium-secure forensic mental health service in South London, UK, covering a diverse geographical area including areas of high poverty and urban deprivation. Staff were eligible to participate if their role involved direct contact with service users. Nonclinical staff were not eligible, as the aim was to understand attitudes toward passive remote monitoring technology in a clinical context. We conducted recruitment and analysis concurrently, and recruitment stopped when we achieved data saturation, the point at which focus groups appeared to stop yielding new themes (Fusch & Ness, 2015).

3.2.3 Focus Group Topic Guide

The topic guide was based on previous studies of mental health staff views around digital health technology (Berry et al., 2017; Bucci et al., 2019), and included issues related to perceived utility, safety and security, and data connectivity requirements (see Appendix 1). The topic guide was developed through consultation with two service user/caregiver advisory groups, a systematic review of the barriers to and facilitators of remote monitoring for healthcare (Simblett et al., 2018), and by incorporating suggestions from senior

management staff in the recruitment site during consultations in the setup phase of this study. This was to ensure that topics relevant to the forensic setting were covered.

3.2.4 Procedure

Ward managers were approached for permission to recruit from their ward and conducted five focus groups in a private room on the participants' respective wards during staff handover meetings (two groups) or at a time convenient for participants (three groups). These discussions were audio recorded and transcribed verbatim, with personally identifiable content omitted, and participants were provided £10 in cash in recognition of their time. We conducted member-checking focus groups for the primary themes with the same participants so they could suggest any amendments they felt were appropriate (Birt et al., 2016). We informed participants that the study was part of a larger project investigating wearable sensors for monitoring the risk of aggression through physical signals. To provide a context for the discussions, we told participants that the focus groups were the first in a series of studies to investigate whether real-time monitoring of psychophysiological signals could assist in the earlier detection of an increasing risk of inpatient aggression. We presented two remote monitoring devices to illustrate the devices (further details about these devices and why they were selected are provided in Chapter 4). One device (E4; Empatica Srl, Milan, Italy) is worn around the wrist and the other (Everion; Biovotion Ltd, Zurich, Switzerland) is worn around the upper arm (**Figure 7**). Although participants were familiar with commercially available wearable devices, these two devices were novel to them.

Figure 7 Empatica E4 (left) and Biovotion Everion (right)

3.2.5 Thematic Analysis

NVivo 12 software (QSR International) facilitated thematic analysis by two independent raters (BG and KN). Both read and reread the transcripts, producing a list of initial codes, and then independently collated the codes into a list of candidate themes and subthemes. Both

raters' initial identification of individual codes and overall themes were compared, resulting in an initial agreement rate of 59% and 72% for individual codes and overall themes, respectively. Where there were discrepancies (e.g. one rater identifying a code or theme that the other had not), both raters discussed these ratings until they reached a consensus, and themes were revised into their final structure.

3.3 Results

3.3.1 Participant Demographics

From January to March 2019 we approached 43 staff, and 25 of took part in the focus groups. Those who declined did so because of the focus group timing (*n*=9), or they were required to remain on the ward to maintain minimum staff numbers and carry out clinical duties (*n*=4); five did not specify a reason. A total of 18 participants were also available to take part in the member-checking focus groups. **Table 5** presents participants' demographics. We identified five primary themes, which we discuss below in addition to subthemes. **Figure 8** provides a visual overview of these themes and subthemes.

Table 5 Participant demographics

Characteristics	Focus group					Total (N=25)	Member-checking groups (N=18)
	1 (n=6)	2 (n=6)	3 (n=4)	4 (n=5)	5 (n=4)		
Age (years)							
Mean (SD)	37.8 (12.4)	39.5 (11.3)	37 (10.8)	55.4 (7.4)	44.5 (5.1)	42.7 (11.6)	44.4 (12.8)
Range	22-54	25-57	25-51	44-64	41-52	22-64	22-64
Sex, n							
Women	3	6	3	3	1	16	12
Men	3	0	1	2	3	9	6
Ethnicity, n							
Black African	4	0	4	4	4	16	15
Black Caribbean	1	3	0	1	0	5	1
White British	1	3	0	0	0	4	2
Job title, n							
Staff nurse	5	6	1	4	4	20	16
Student nurse	1	0	2	0	0	3	1
Ward manager	0	0	1	1	0	2	1
Highest educational attainment, n							
Higher-level qualification (e.g. university degree, professional qualification)	5	6	2	5	4	22	17
Secondary (A-level equivalent)	1	0	2	0	0	3	1
Time in post (years), Mean (SD)	5.4 (3.4)	5 (4.8)	4 (5.7)	10.8 (4.7)	4.6 (2.1)	6.5 (3.4)	6.4 (4.8)

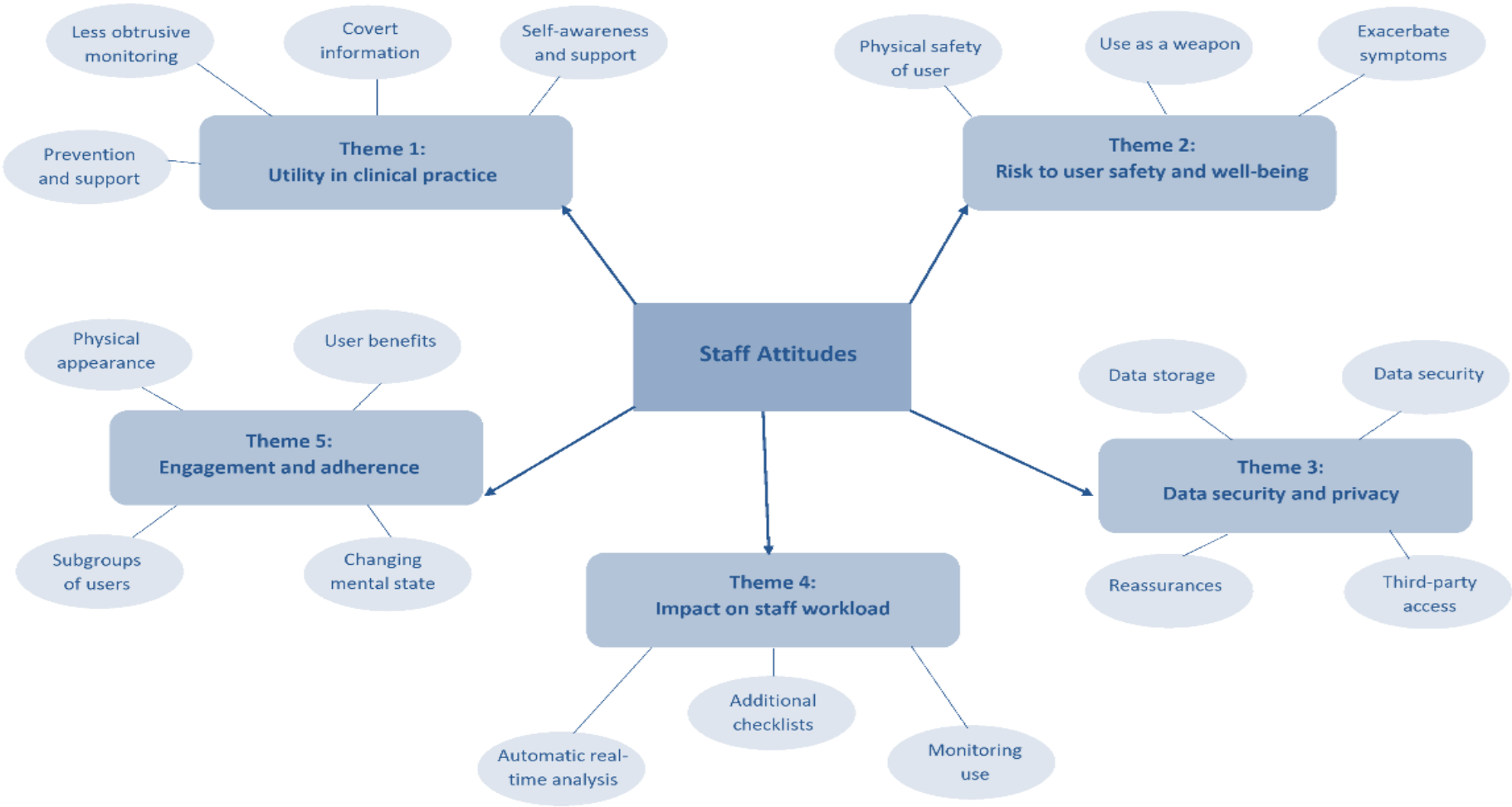

Figure 8 Visual overview of themes and sub-themes

3.3.2 Theme 1: Utility in Clinical Practice

In every focus group, participants identified numerous ways in which using these devices could augment their practices. One area of discussion related to the devices' capacity for ***prevention and support*** to be offered to users:

> *Yeah it would be helpful, it's like an early-warning sign so, when you know that they are coming to be anxious, you find a way of intervening before it escalates*
> *[Participant 023, nurse]*

> *Because sometimes by the time they express it, it means it's, it's already you know, so if we can see ahead of time and monitor it, I think it's good.*
> *[Participant 009, nurse]*

Participants also suggested that these devices could facilitate a ***less obtrusive monitoring*** approach, enabling assessments without the need for staff to be in physical contact with users:

> *Because if a patient is wearing this device even if they are in their bedroom, and they're out of sight of the staff, with the device working you should be able to tell that maybe something has gone wrong...if you just see them physically, they might be in their room they're anxious, they're agitated without you seeing them, you won't be able to tell.*
> *[Participant 024, nurse]*

Reflecting on the seemingly unprovoked nature of some aggressive incidents, participants felt that these devices could provide staff with ***covert information*** that may not otherwise be expressed by the users or observable by staff:

> *...because we did not see it we think it's unprovoked…but with these devices maybe we will know that there's something happening...before the incident, later maybe attacking somebody or something.*
> *[Participant 025, nurse]*

> *...not all our patients will be able to say "oh well I feel agitated" or be able to come out and say it, but within themselves all the physical, you know, changes are taking place so I think it's good, it will help us to see the covert, you know, things that are not outward that the patients cannot express.*
> *[Participant 009, nurse]*

As a result of identifying this covert information, participants felt that this could be used to foster ***self-awareness and support*** among users, and augment an anger management program offered to users:

> *...[to the] point of anger exactly.*
> *[Participant 015, nurse]*

...this would be a different way of reminding them, maybe this would be a reminder. Because, um, if somebody has done anger management and he knows that by the time he starts breathing heavily, or by the time he feels he's getting, um, a bit sweaty or agitated and getting wound up...they should disengage. And they have not been doing that because they still don't have the capacity to do that because they don't, um, how can I say, they can't get themselves to...take themselves away from aggression. So, what this would do is to then remind them that this is what they need to do, for some of them who have done anger management.
[Participant 017, nurse]

3.3.3 Theme 2: Risk to User Safety and Well-Being

Participants in four focus groups discussed the impact of the devices in relation to the ***physical safety of the user***. One focus group cited the risk of the device being used as a ligature as a concern, due to the elastic armband of one of the devices:

...how far does it stretch, can you put it round your neck?
[Participant 008, nurse]

Oh yeah, you could I reckon, you could stretch it.
[Participant 011, nurse]

Well that might be an issue, you know, ligatures.
[Participant 008, nurse]

The possibility that the devices could be ***used as a weapon*** was another risk that participants raised, with one focus group discussing the potential implications of one of the devices having an elastic armband:

...should be something that they cannot use as a weapon, like, there shouldn't be any metal or something that they can use to self-harm.
[Participant 025, nurse]

You could use this [referring to device] as a weapon like a slingshot.
[Participant 011, nurse]

Participants suggested that users' mental well-being would need to be considered in addition to their physical safety when wearing the devices. Specifically, participants raised concerns that continuous monitoring could ***exacerbate symptoms*** of paranoia among some users:

They might think that you are monitoring, that you are controlling their mind, controlling their mental state, all of this, so it might make more paranoia.
[Participant 003, nurse]

When you give this to a paranoid patient they will think you are monitoring them. It will be so difficult to explain it to them to understand it that this is what you're monitoring....This paranoia could also lead to them not even wearing this.
[Participant 015, nurse]

3.3.4 Theme 3: Data Security and Privacy

Across three focus groups, participants discussed the measures in place to ensure that data collected by the devices would be kept secure and confidential. Participants wanted to know, in advance, specific details concerning ***data storage***: where the information collected by the devices would be stored and who would have access to it; ***data security***: what protections would be in place to keep the data private and confidential; and ***access by third parties***: whether data would be shared with other individuals or companies:

> *...you know I'm gonna need to know, um, what [inaudible] they do, how, even if you say the data is gonna be stored, how secure is the storage, can it be hacked, you know, cos this is like really private, um, information.*
> *[Participant 002, nurse]*

> *Yeah I think we'd want reassurance, wouldn't we, that the information we give is protected confidential and it'd be the same for the patients, know how it's going to be used and...just make sure it's anonymized the data.*
> *[Participant 008, nurse]*

> *You know is it gonna be sold to a third-party like we've seen with social media now where obviously data protection is like a lot*
> *[Participant 002, nurse]*

Because of these concerns, participants felt that ***reassuring users*** that their data would be kept secure would be necessary, particularly due to the risk of exacerbating symptoms of paranoia discussed in Theme 1:

> *Just reassuring them that their data will not go anywhere, it's just for the ward, because some of them will be paranoid.*
> *[Participant 025, nurse]*

One participant made a practical suggestion as to how users could be reassured, drawing parallels with a ward policy whereby staff model appropriate eating during mealtimes. They suggested that staff members wearing the devices themselves could reassure users:

> *...each time they are eating you need to have 2 staff that will come and model and sit with them...so I'm just thinking that maybe they can try to [inaudible]. If they are wearing it that they see staff wearing it as well, they won't be thinking about confidentiality, maybe they are trying to take their information or do something else.*
> *[Participant 024, nurse]*

3.3.5 Theme 4: Impact on Staff Workload

While identifying ways in which these devices could be implemented in clinical practice, participants in three focus groups also highlighted that this should not increase staff

members' already high workload. Participants stressed the need for ***automatic real-time analysis*** of the data collected by the device, to ensure that information can be acted on without additional burden on staff time:

> *Yeah I mean that's the only way I can think it'd be useful, without that real-time information, we're gonna have to take the watch and then upload the data and see what's going on.*
> *[Participant 002, nurse]*

> *Yeah [if] it's automatic, and we don't have to put in a lot more to get the data and to analyse the data, then it will be good, yeah. But if we have to put in a lot more to measuring and analysing the data and doing deductions for ourselves, that means additional work to do.*
> *[Participant 009, nurse]*

Participants also questioned whether ***additional checklists*** would accompany the devices, increasing the level of ongoing input required from staff:

> *So does this come with a pack or a checklist or something that you've got to fill it out every day during the monitoring, or will you really only attend to it when you, it gives you any signals or something that there are any changes? How is it done, I'm just thinking if it's something that's supposed to be monitored every now and then and every day it means additional work, isn't it, you feel, more boxes to tick.*
> *[Participant 009, nurse]*

Responsibility for ensuring that users are wearing the devices was also discussed, with participants feeling that it would fall to staff to spend additional time ***monitoring use***, therefore taking time away from their other duties:

> *Because it's going to be more [inaudible] on staff now. Now they are wearing it they are gonna say, oh, gonna spend a couple of minutes encouraging them to put it on or go put it on, so it's going to take valuable time out of your working day, so, it's going to be time consuming in a way.*
> *[Participant 001, nurse]*

3.3.6 Theme 5: Engagement and Adherence

All focus groups discussed the numerous factors that may affect the likelihood of users engaging with the devices. The ***physical appearance*** of the device, including overall size and possible resemblance to a tracking device, was one factor:

> *And you know this one [referring to device] is so conspicuous it looks so much like a tracking device, you know*
> *[Participant 009, nurse]*

> *...even if they have the reservations about, "oh we don't want to be monitored" and things like that, if they see something that looks a bit stylish they might be more*

prone to wear it.
[Participant 018, nurse]

Participants also suggested that users would be more likely to engage with the devices if there was a clear ***benefit to the user***:

If there's nothing for them they won't take it.
[Participant 017, nurse]

One benefit that participants felt would appeal to users was whether wearing the devices would positively affect their leave status:

But then I'm thinking it's one thing, how is it gonna directly benefit them, like, "what are you gonna tell if I'm a patient, and you wanna give me this I need to know, like...is it gonna make my leave better
[Participant 002, nurse]

A total of four focus groups discussed the impact that ***changing mental state*** would have on users' engagement, suggesting that ***subgroups of users*** may be most likely to engage:

...that would be a problem, getting them to volunteer for it and, um, making sure they understand completely, cos some people are more paranoid on days...than other days so it could be they're fine for 5 days then the sixth day they're really paranoid
[Participant 008, nurse]

The most settled patients there, they will cooperate, some of them are, so most of them that are eager to go out they'll cooperate, but this ones, like, very paranoid like you said, you will have a tough time.
[Participant 001, nurse]

3.4 Discussion

To our knowledge, this is first study to investigate the attitudes of frontline staff members in inpatient forensic mental health toward passive remote monitoring for risk of aggression. Overall, staff suggested this technology could benefit their risk assessments, identifying changes in risk factors that would otherwise not be identified though current methods. The real-time stream of information provided by this technology could facilitate just-in-time support before behaviour escalated into aggression. However, staff also raised numerous implementation barriers, including the physical safety of the user and security of their personal data, negative impact on staff workload, and engagement barriers.

3.4.1 Advantages of Passive Remote Monitoring

Participants suggested that the *"covert"* information monitored by this technology could help to explain the seemingly unprovoked nature of some aggressive incidents they

encounter. Current risk assessments require staff to rate risk based on service users' visible presentation (e.g. irritability and not following instructions; Ogloff & Daffern, 2006), meaning potentially relevant information concerning their psychophysiological arousal cannot be factored into these assessments. Passive remote monitoring technology could therefore provide an additional source of relevant data to support existing assessments, consistent with previously hypothesized benefits of digital technology in forensic mental health services (Tully et al., 2015). Acquiring an additional, objective source of data could also circumvent known limitations of structured risk assessments, such as rater bias (Zapf et al., 2018).

Participants reported that passive remote monitoring technology could provide them with prior knowledge of when users may be experiencing difficulties, thereby facilitating appropriate and timely support. Participants discussed this in relation to staff-initiated de-escalation procedures, but also identified a role for the technology to foster self-awareness and self-management among users. This suggestion is consistent with previous studies of staff views around the role of technology in mental health (Berry et al., 2017; Bucci et al., 2019). Encouraging service users to recognise and reflect on their individual warning signs is also consistent with clinical guidelines for managing aggression (National Institute for Health and Care Excellence, 2015), and supported by previous research indicating an overreliance on staff-initiated de-escalation (Kuivalainen et al., 2017).

Enabling users to be monitored without the need for in-person observation was considered less obtrusive than current observation practices. Enhanced observation procedures (e.g. eyesight and arm's-length observations) are employed for service users at high risk of aggression (NICE, 2015), but are experienced negatively by both service users and staff (Cox et al., 2010). Passive remote monitoring technology could therefore enable monitoring with fewer physical restrictions and demands on staff resources. This would need to be balanced against the accuracy and range of clinical observations that can be made through technology alone. For example, peer interactions and negative attitudes are relevant risk factors for aggression (Papadopoulos et al., 2012) but cannot be assessed through actigraphy or biosensors alone, highlighting the need for multiple sources of observation data. Overreliance on technology could also limit the opportunity for physical service user–staff interactions and dialogue, which are an integral component of effective therapeutic relationships (McAndrew et al., 2014). This is also a concern shared by previous studies of staff views around digital health technology (Bourla et al., 2018; Bucci et al., 2019). However, as mentioned in one focus group, staff awareness of when changes are detected by the

passive remote monitoring technology could also facilitate dialogue and staff–service user interaction (*"I could see that it could be useful, because, um, it could just be a point of engagement for staff"* [Participant 017, nurse]).

Participants suggested that passive remote monitoring technology might only be suitable for subgroups of users, determined by their current mental state and paranoid ideation towards the technology. This reflects the need for a personalised approach which balances the potential benefits to the user (e.g. improved understanding of changes in risk state) and challenges (e.g. difficulties with engagement). A previous evaluation of a passive remote monitoring system (a global positioning system [GPS] tracker) in a forensic mental health service adopted a similar subgroup approach (Tully et al., 2016). The GPS system in this study was intended primarily for use by subgroups of service users at the early stages of their leave period or during specific periods of transition, rather than all service users.

While highlighting the potential benefits of passive remote monitoring technology, no participants suggested that technology should replace the practice of staff-completed risk assessments. This is consistent with previous research reporting universal agreement among staff that digital health care technologies should be an adjunct to traditional care rather than a replacement, as replacement could be detrimental to user well-being and therapeutic relationships (Bucci et al., 2019). Future use of passive remote monitoring technology should therefore be considered as a component of a blended approach that complements, but does not wholly replace, staff-completed structured risk assessments.

The issues discussed above are hypothesized benefits, and while there is potential for passive remote monitoring technology to support risk management for aggression, this needs to be supported by high-quality empirical evidence. Key issues that need to be addressed include the feasibility and acceptability of this technology for end-users, whether a reliable psychophysiological signature for aggression exists, the accuracy of the data provided by this technology, including the ability to correctly identify changes related to aggression and to rule out those that are unrelated, and what support and de-escalation procedures (if any) should be initiated based on the data received.

3.4.2 Implementation Barriers

Participants identified numerous issues that are likely to affect successful implementation of passive remote monitoring technology. The physical safety concerns raised, relating to ligature risk and use as a weapon, appeared to be linked to a specific design characteristic

(elastic armband) of a device presented during the focus groups. This highlights the importance of considering the physical design of passive remote monitoring technology intended for use in inpatient services, where physical safety and risk of self-harm are management priorities. Concerns were raised that continuous monitoring may exacerbate symptoms of paranoia, consistent with concerns raised in Bourla et al. (2018) regarding exacerbating symptoms of anxiety. While previous studies in the community indicate the acceptability of passive remote monitoring for individuals with psychosis (Cella et al., 2018, 2019; Meyer et al., 2018), it may be a pertinent issue for those involuntarily admitted to inpatient services and experiencing loss of control and restrictive practices (McGuinness et al., 2018). Establishing trust with users beforehand and evaluating whether adverse effects do arise as a consequence of monitoring, is therefore likely to be integral to successful implementation.

Consistent with previous research among staff (Breedvelt et al., 2019; Huckvale et al., 2019) and service users (Boonstra et al., 2018), participants expressed data privacy concerns. The specific concerns related to three areas where they would require adequate assurance to be comfortable using passive remote monitoring: data storage, security, and accessibility by third parties. Addressing these concerns in the long term will require transparency from digital health companies about the procedures in place for handling user data, and to ensure that users have access to this information. In the shorter term, participants reported that staff could play an important role in providing reassurance to users. The suggestion that staff could lead by example by trialling the devices themselves reflects the role of staff as positive role models in inpatient services (Marshall & Adams, 2018) and is a practical approach to alleviating user concerns.

Participants expressed concern that incorporating passive remote monitoring technology into their working practice might negatively affect their existing workload. Like Bucci et al. (2019), participants were concerned with the potential burden of handling and analysing large volumes of real-time data and emphasised that these devices need to be complemented by automatic real-time analysis. While this would address the process of analysing the raw data into an actionable format, it is possible that a constant stream of processed data could still prove overwhelming. Establishing an appropriate format for presenting the data, balancing the frequency, level of detail, and staff capacity to act on this information, would therefore be required. Participants also highlighted practical considerations such as the introduction of additional checklists and questioned where

responsibility for monitoring use would lie. Future use of passive remote monitoring technology would need to balance potential clinical benefits with practical implementation issues, to ensure that they support and not hinder clinical care. Machine learning algorithms processing data in real-time, presented in a user-friendly and actionable format would be an option, and participants discussed presenting the data as a visual display in the ward's central nursing office. Embedding a dedicated technology specialist within the clinical team could also be considered (Noel et al., 2019).

3.4.3 User-Centred Design

Achieving the hypothesised benefits of passive remote monitoring technology requires adequate levels of staff and service user engagement. This study highlighted multiple areas which may affect engagement, which in turn demonstrates the need for a user-centred design approach to address these. For example, the influence of a device's physical appearance on engagement highlights the importance of involving users in the choice and, ideally, design of devices, as individual preferences may vary. Exploring how monitoring might benefit users, such as less restrictive management practices, could also have a positive effect on engagement. Staff enthusiasm and confidence to work with novel digital technologies is essential, and previous research identified barriers to organizational change in mental health services including poor job satisfaction, burnout, and lower levels of experience (Laker et al., 2014, 2019). These may also be barriers to the successful introduction of passive remote monitoring technology, and engagement with staff to explore and overcome these will be required.

3.4.4 Strengths and Limitations

This study took place in a hospital where passive remote monitoring technology, GPS tracking devices, has been in use for several years to monitor leave (Murphy et al., 2017; Tully et al., 2016). Participants' responses may have been influenced by this prior experience, and so may not necessarily reflect the views of those unfamiliar with these systems. However, some familiarity might also have facilitated discussion, with the issues and recommendations raised reflecting participants' applied experience of passive remote monitoring. Because this is a medium-secure forensic mental health service, the themes identified in this study may not necessarily generalize to forensic services with higher levels of security (e.g. where more stringent policies for patient access to digital equipment exist), or to non–forensic mental health services, where inpatient aggression also occurs.

This study was conducted from the epistemological position that the meanings arising out of participants' discussions reflected reality. It is important to acknowledge however that the researcher's own position, experience and knowledge may have influenced the interpretation of these findings (Mosselson, 2010). For example, BG has previously worked in both forensic mental health services and digital health research, which may have shaped his interpretation of the focus group discussions. BG's position as a PhD student with a series of planned studies may have also exerted an influence, as later studies would be influenced by the findings of this study. For these reasons care was taken not to influence the course of the focus group discussions or their subsequent interpretation. This included generating a focus group topic guide in consultation with service users, independent coding by KN, and member checking focus groups with original participants to guard against the influence of any *a priori* expectations regarding the outcome of the focus groups.

The views of senior nursing and managerial staff might have provided greater context to wider organisational challenges associated with passive remote monitoring technology (e.g. infrastructure requirements and financial costs). These staff were present in smaller numbers, and we may not have successfully captured their views. Including only members of the nursing staff may have limited the emergence of new themes. For example, the technical infrastructure requirements for remote monitoring technology could be clarified by seeking the views of support service staff (e.g. technicians and engineers). The time for focus groups was restricted, and this might also have limited the emergence of new themes. However, the replication of themes across the different groups makes this unlikely.

3.5 Chapter Conclusion

This study outlines how passive remote monitoring technology could offer numerous benefits to monitoring the risk of aggression in inpatient forensic mental health services from the perspective of staff working within these services. Multiple points related to feasibility and acceptability were raised, therefore it was considered prudent to conduct an initial pilot study (see Chapter 4). Another key theme raised by staff related to the clinical utility of remote monitoring, particularly the potential to identify relevant changes in risk factors before this escalated into aggression. Chapters 6, 7 and 8 present the results of studies conducted with service users to investigate this possibility.

Many findings in this study also reflect issues which are beyond the scope of this thesis but should be addressed in future research. For example, participants identified a range of implementation barriers that need to be overcome to integrate remote monitoring

effectively into current working practice. This reflects a wider issue in the literature with most novel prediction models in mental health failing to progress to the implementation stage (Salazar de Pablo et al., 2020). Establishing appropriate policies and standards for data protection represents another key hurdle for the wider use of remote monitoring, requiring collaboration between service users, healthcare staff, researcher and digital health organisations (Torous et al., 2019). These issues and recommendations for future research are discussed in greater detail in Chapter 9.

Chapter 4 : A Pilot Study of Remote Monitoring Within Forensic Mental Health Services

4.1 Introduction

The staff focus groups conducted in the previous chapter raised numerous considerations related to the acceptability and feasibility of remote monitoring in forensic mental health services. While developments in healthcare technology and remote monitoring methods have expanded, rates of adoption have not (Velthoven & Cordon, 2019). One of the key reasons for the disparity between development and hopes for novel monitoring approaches on the one hand and end-user uptake on the other is whether the monitoring method is acceptable to end-users (Simblett et al., 2018).

Sustained engagement with novel healthcare technologies and monitoring methods is dependent on end user acceptability, but this issue has been neglected in the research literature. For example, a systematic review of inpatients' perceptions and experience of using wearable vital sign monitoring equipment reported a limited evidence base and recommended investigation of these issues as a research priority (Sprogis et al., 2019). Factors which end-users have reported as affecting their perception of the acceptability of a remote monitoring method include their levels of satisfaction and enjoyment (Park, 2020), and an understanding of the benefits the monitoring method offers to their health and wellbeing (Yang et al., 2016).

As highlighted by participants in the staff focus groups reported in the previous chapter, feasibility and accuracy of novel remote monitoring methods is also a key consideration for potential use in healthcare settings. For example, the high volume of data which passive remote monitoring technology enables is accompanied by a high rate of data artefacts. Photoplethysmography (PPG), a sensor used for HRV measurements which most passive remote monitoring technology uses, is particularly sensitive to artefacts caused by physical motion (Schuurmans et al., 2020). Previous studies using passive remote monitoring technology have reported that in some cases over 75% of recorded data were identified as artefacts (van Lier et al., 2020). If left unchecked these artefacts are likely to render any statistical analysis unreliable and potentially inaccurate.

Previous research investigating ESM and passive remote monitoring technology in forensic mental health settings is limited, and to our knowledge there have been no previous studies

investigating the feasibility (in terms of data quality and accuracy) and acceptability of these monitoring methods to end users. While ESM and passive remote monitoring may offer a range of potential benefits for assessing risk of aggression, these cannot be realised if the monitoring methods themselves are inaccurate and/or not acceptable to users. Therefore, the aim of this study was to investigate the acceptability and feasibility of the experience sampling and passive remote monitoring methods.

4.2 Method

4.2.1 Ethical Approval

Ethical approval was obtained from the Wales Research Ethics Committee 5 (ref: 18/WA/0219) on 18th October 2018 and Health Research Authority on 23rd October 2018. Research and Development approval was granted by South London and Maudsley NHS Foundation Trust (ref: R&D2018/078) on 6th November 2018.

4.2.2 Participants

Participants were staff and service users in a medium-secure forensic mental health service in South London, UK. Staff were eligible to participate if their role involved direct contact with patients and all five wards in this service were approached and consented to take part. Service users were eligible to participate if they possessed capacity to consent and if participation would not disrupt their care. These eligibility criteria were determined by participants' Responsible Clinician.

4.2.3 Measures

4.2.3.1 Experience Sampling Methodology

Nineteen ESM questions were used in this study, assessing multiple domains including affect, social interaction and aggressive ideation (see **Table 6**). These questions were selected from a three-stage development process. First, the systematic review discussed in Chapter 2 identified candidate risk factors based on their statistical associations with aggression and the quality of the study. Second, discussions were held with forensic mental health service users to confirm the relevance of the candidate factors/identify new factors, in addition to providing input into the conduct of the study. Third, two separate service user and carer advisory groups were consulted about a provisional ESM diary protocol to confirm the procedure was relevant and understandable. All ESM items were scored on a seven-point Likert scale (1=Not at all – 7=Very much so) and were provided to participants in the form of a paper diary. Participants received seven prompts each day for seven consecutive days (49 prompts in total) through a pre-programmed wristwatch.

4.2.3.2 Psychophysiology

The two passive remote monitoring devices presented to participants in the earlier qualitative staff study (Empatica E4 and Biovotion Everion) were used in this study (see **Table 7** for their technical details). These devices were chosen following consultation with researchers in a large multinational study of passive remote monitoring technology (RADAR-CNS; Matcham et al., 2019) and after considering previous research which had used these devices. The E4 has been used in a variety of clinical populations in both inpatient and community settings (Cella et al., 2019; Kleiman et al., 2019). Validation studies comparing the E4 to laboratory-based assessments of electrodermal activity and HRV have confirmed the E4's accuracy for these measures (McCarthy et al., 2016; Ollander et al., 2016; Pietilä et al., 2018; Ragot et al., 2018). The Everion is a relatively new device compared to the E4 but has been used in community settings in relation to physical health (Keogh et al., 2020; Pavic et al., 2020; Simblett et al., 2020) and has undergone validation studies (Barrios et al., 2019; Bent et al., 2020).

Table 6 Experience Sampling Methodology Questions

Right now, I feel []
1. Cheerful
2. Irritated
3. Angry
4. Insecure
5. Like others are out to get me
6. Relaxed
7. Guilty
8. Confused
9. Restless
10. Anxious
11. Lonely
12. Satisfied
13. I don't want to be around other people
14. Down
15. My mental health is good
Since the last beep, have you []
16. Talked or interacted with other people on the ward, not including staff
17. (if yes) Do you think this was a positive interaction
18. Talked or interacted with staff on the ward
19. (if yes) Do you think this was a positive interaction
20. Taken part in any exercise or done any physical activity which made you out of breath
21. (if yes) Can you remember roughly what time this started and finished
Since the last beep, have you []
22. Felt like you could hit someone/something
23. Felt like you could raise your voice or shouted as someone

Table 7 Passive remote monitoring device technical details

Device Details	Empatica E4	Biovotion Everion
Recording Location	Wrist	Upper Arm
Electrodermal Activity		
Method of Recording	2 Silver-Plated Electrodes	2 Silver-Plated Electrodes
Sampling Frequency (Hz)	4	10
Heart Rate Variability		
Method of Recording	Photoplethysmography	Photoplethysmography
Sampling Frequency (Hz)	64	51.2
Physical Motion		
Method of Recording	3-Axis Accelerometer	3-Axis Accelerometer
Sampling Frequency (Hz)	32	50

4.2.3.3 Acceptability

An eight-item user-experience questionnaire assessed the acceptability of the ESM and passive remote monitoring procedures. Questions were rated on a seven-point Likert scale (1 = Not at all; 7 = Very much so) and included a free-text response section for additional qualitative feedback. The questionnaire was created for this project in order to capture acceptability issues relevant to both ESM and passive remote monitoring. The questionnaire items were based on a systematic review of the barriers and facilitators to remote monitoring technology (Simblett et al., 2018) and the System Usability Scale (Brooke, 1996). A technical log sheet was also provided for participants to record the date, time and specific details of any technical issues encountered during the study.

4.2.4 Procedure

Following informed consent participants were randomised to receive either the E4 or Everion device. Participants were provided with comprehensive instructions for operating their device and asked to wear it each day during their normal waking hours for seven consecutive days, taking it off only to bathe and sleep and to keep the device charged. During the study, participants were contacted in-person or by telephone at least twice to ensure adherence to the protocol and address any issues. Because there was no Bluetooth connection in the inpatient environment and recording data could not be streamed in real-time, both devices

were operated using their internal memory mode in which recordings were saved to the device's flash memory. To ensure there was sufficient memory for participants' recordings a new device was provided to each participant midway through their participation.

4.2.5 Analysis

An acceptability threshold for study completion was set at 60% valid ESM and passive remote monitoring data, consistent with previous research of remote monitoring in healthcare staff (Burch et al., 2019). Staff and service users results from the user-experience questionnaires were analysed using Mann-Whitney U tests and repeated measures ANOVAs. Experience Sampling Methodology adherence and passive remote monitoring device usage were analysed descriptively and artefacts in the passive remote monitoring data were identified in Kubios (Lipponen & Tarvainen, 2019).

4.3 Results

Fifty-two staff were approached and 35 consented to participate. Nine had previously participated in the earlier qualitative staff study. Those who declined to participate reported not wanting to wear the device during working hours (*n* = 4) or did not specify a reason (*n* = 13). Nine service users were approached and six consented, with the three who declined not specifying a reason for this. Participant demographics are reported in **Table 8**.

Table 8 Participant demographics

Characteristics	Total (N = 41)	Staff (N = 35)	Service Users (N = 6)
Age (years)			
Mean (SD)	37.32 (11.77)	38.66 (11.85)	29.50 (8.26)
Range	18 – 64	22 – 64	18 – 43
Gender			
Women	24	24	0
Men	17	11	6
Ethnicity			
Black African	26	22	4
Black Caribbean	6	4	2
White British	4	4	0
Other White Background	3	3	0
Asian British	2	2	0
Job role			
Staff Nurse	-	25	-
Ward Admin	-	5	-
Occupational Therapist	-	5	-
Years in post			
Mean (SD)	-	5.41 (4.29)	-
Range	-	1-16.42	-

4.3.1 Acceptability of Passive Remote Monitoring

No participants reported premature termination of their monitoring periods as a result of technical difficulties. **Figure 9** and **Figure 10** illustrate the staff responses to the user-experience questionnaires for both devices. There were no statistically significant differences between devices in the questionnaire items (all *p*'s >.05). For the Empatica E4 all items, except for battery life, were rated as highly acceptable by at least 50% of participants. For the Biovotion Everion only three items (fitting with daily routine, receiving sufficient training to use the device and being easy to remember) were rated as highly acceptable by at least 50% of participants.

Figure 11 and **Figure 12** illustrate service users' responses to the user-experience questionnaires for both devices. There were no statistically significant differences between devices in the questionnaire items (all *p*'s >.05) except for fitting in with participants' daily routine, where the Empatica E4 was rated as significantly better ($F(1, 5) = 25.00$, $p = .038$). While not statistically significant, no participants reported malfunctions with the Empatica E4 while two participants recorded technical difficulties with the Biovotion Everion on several occasions. The technical log sheet indicated that these were difficulties in turning the

device on/off using its infrared sensor, in addition to periods where the device would briefly and periodically vibrate at random periods while being worn.

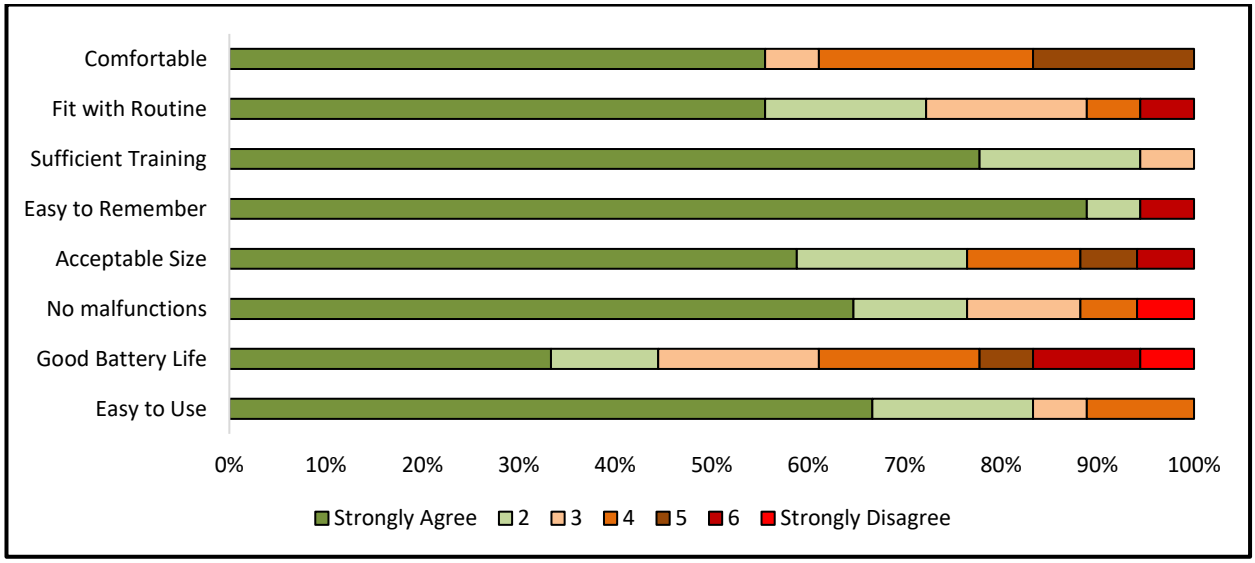

Figure 9 Staff user-experience survey responses - Empatica E4 (N=18)

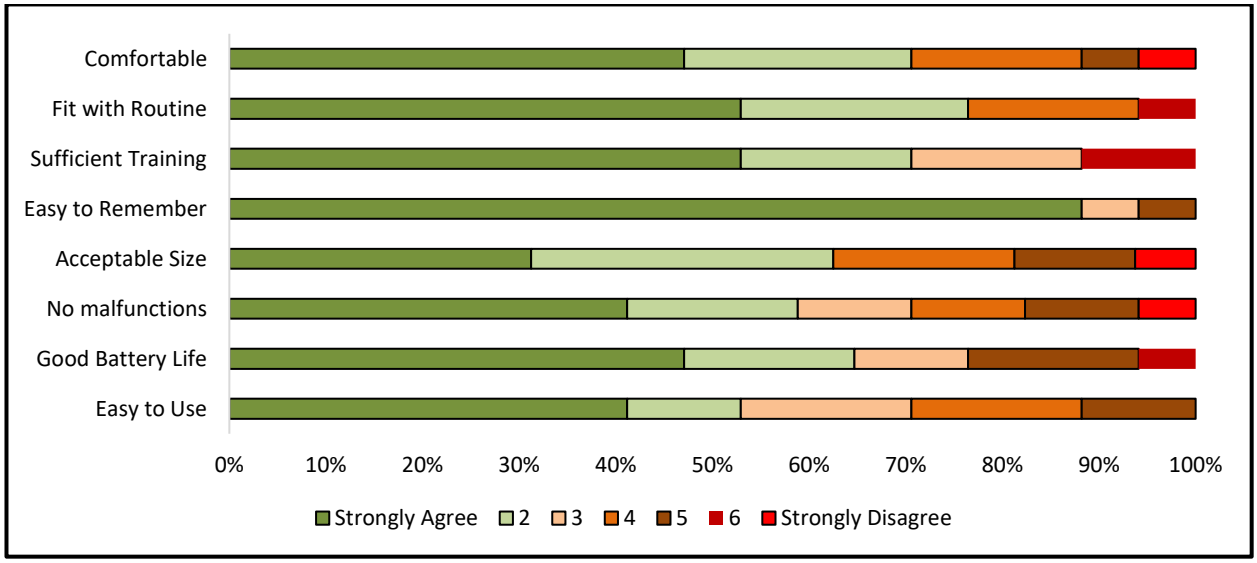

Figure 10 Staff user-experience survey responses - Biovotion Everion (N=17)

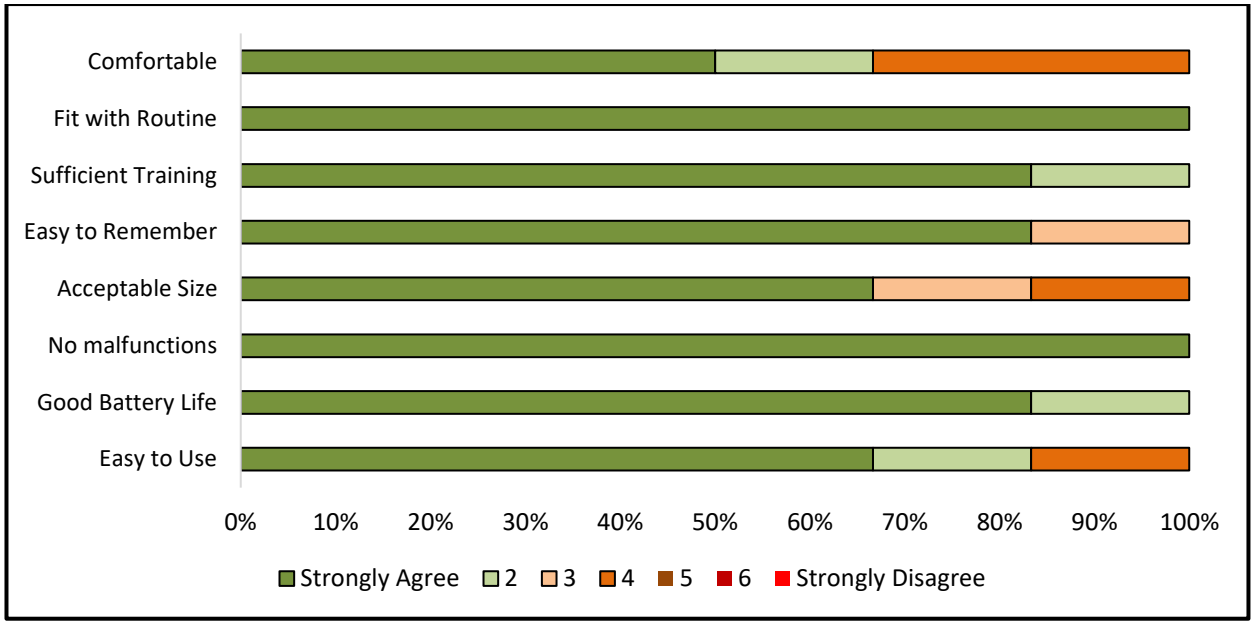

Figure 11 Service user eser-experience survey responses - Empatica E4 (N=6)

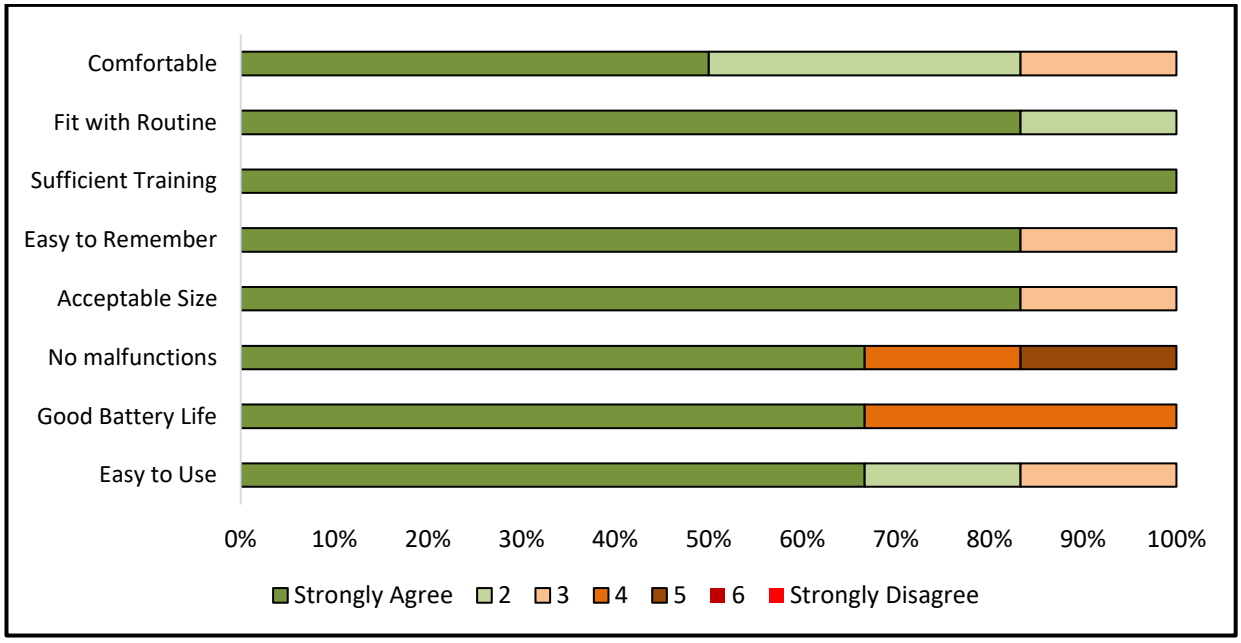

Figure 12 Service user user-experience survey responses - Biovotion Everion (N=6)

4.3.2 Adherence to Passive Remote Monitoring and Data Quality

Figure 13 and **Figure 14** illustrate the average device use over the week by staff and service users, respectively. There were no statistically significant differences in device usage among either staff or service users (all *p*'s >.05). Both figures illustrate a similar pattern of initially greater engagement with the Empatica E4 compared to the Biovotion Everion which increased steadily over time, with both devices reaching a similar peak usage around days 4-5. As expected from previous research, device use declined in the final days of participation among both staff and service users and for both devices.

The data quality for both devices based on the identification of artefacts was acceptable but indicated significantly higher quality in the Empatica E4. For the PPG data from which HRV is calculated, 40% of the Empatica E4 dataset and 48% of the Biovotion Everion dataset was identified as an artefact (p = .043). For the EDA sensor 37% of the Empatica E4 dataset and 45% of the Biovotion Everion dataset was identified as an artefact (p = .039).

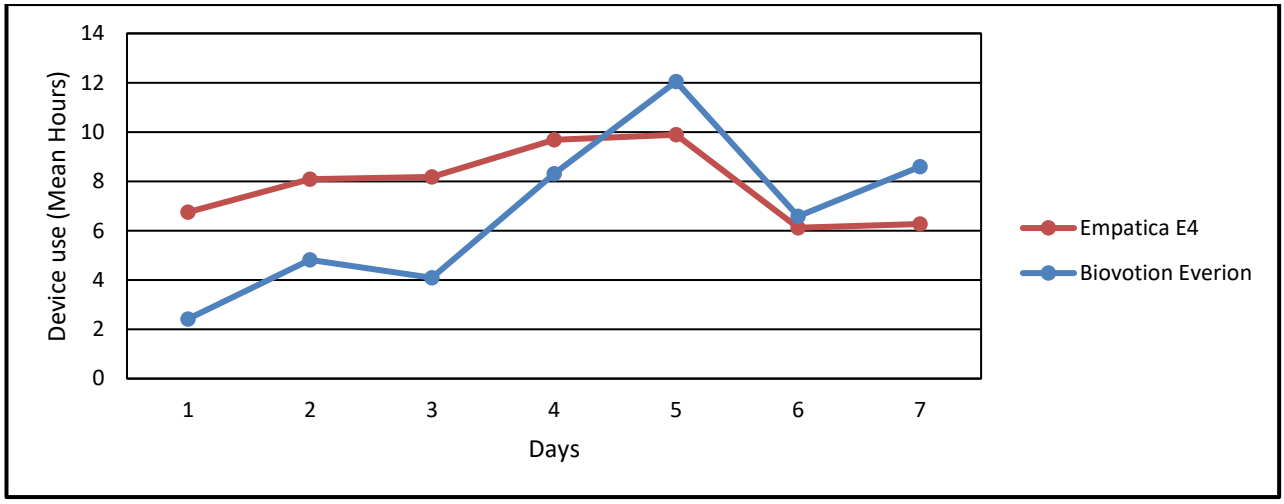

Figure 13 Passive remote monitoring device use – staff (N=35)

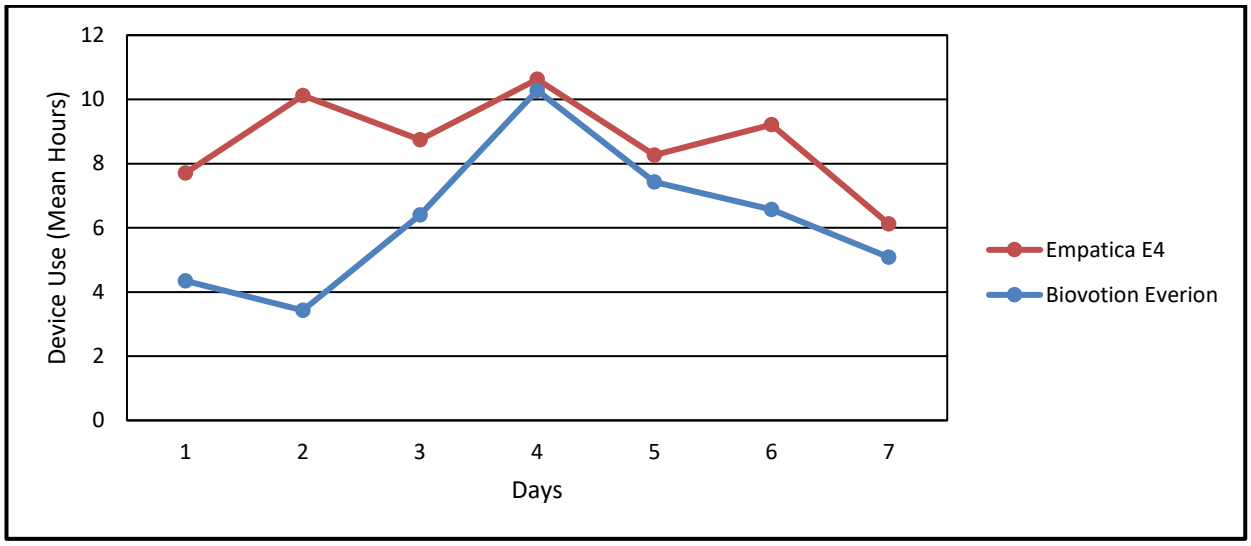

Figure 14 Passive remote monitoring device use - service users (N=6)

4.3.3 Acceptability and Adherence to Experience Sampling Methodology

Figure 15 illustrates service users' ratings of the acceptability of the experience sampling method. Each item in the questionnaire was rated as highly acceptable by 60% of participants, with no participants reporting that completing the questionnaires interfered with their normal daily activities. **Figure 16** illustrates that average completion rate for the ESM prompts across each day in the study. Consistent with previous research, completion rates declined over the course of the study, but still resulted in an overall high completion rate of 69% at the end of the study.

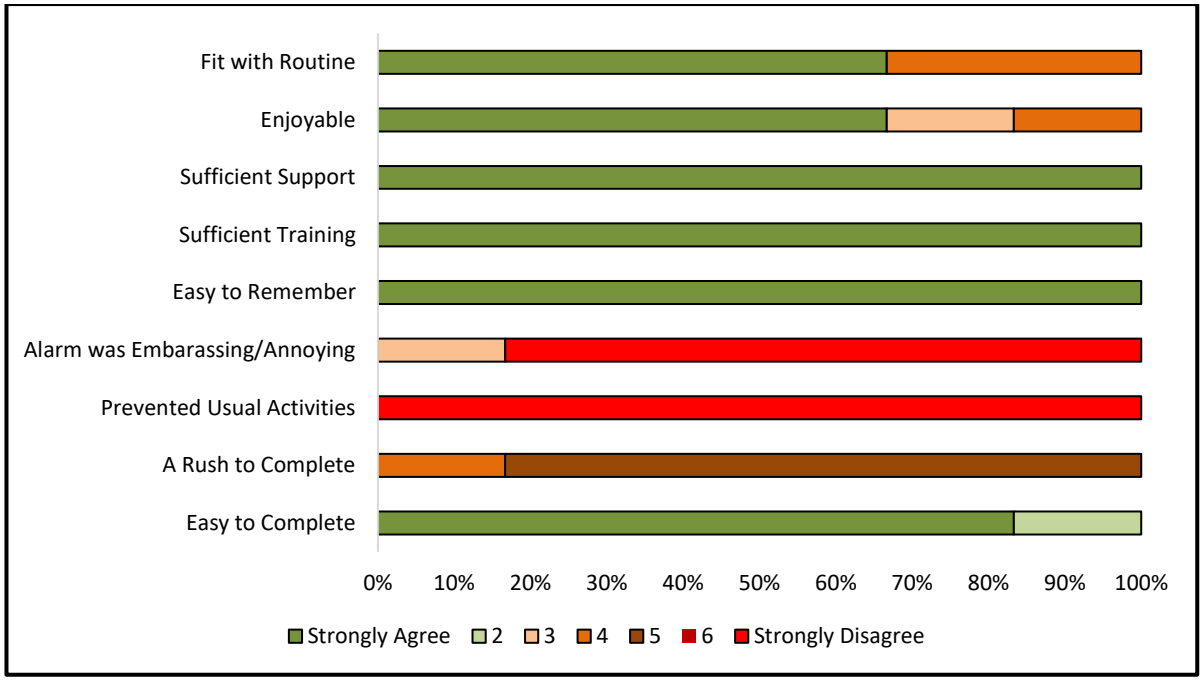

Figure 15 Service user user-experience survey responses for the experience sampling method (N=6)

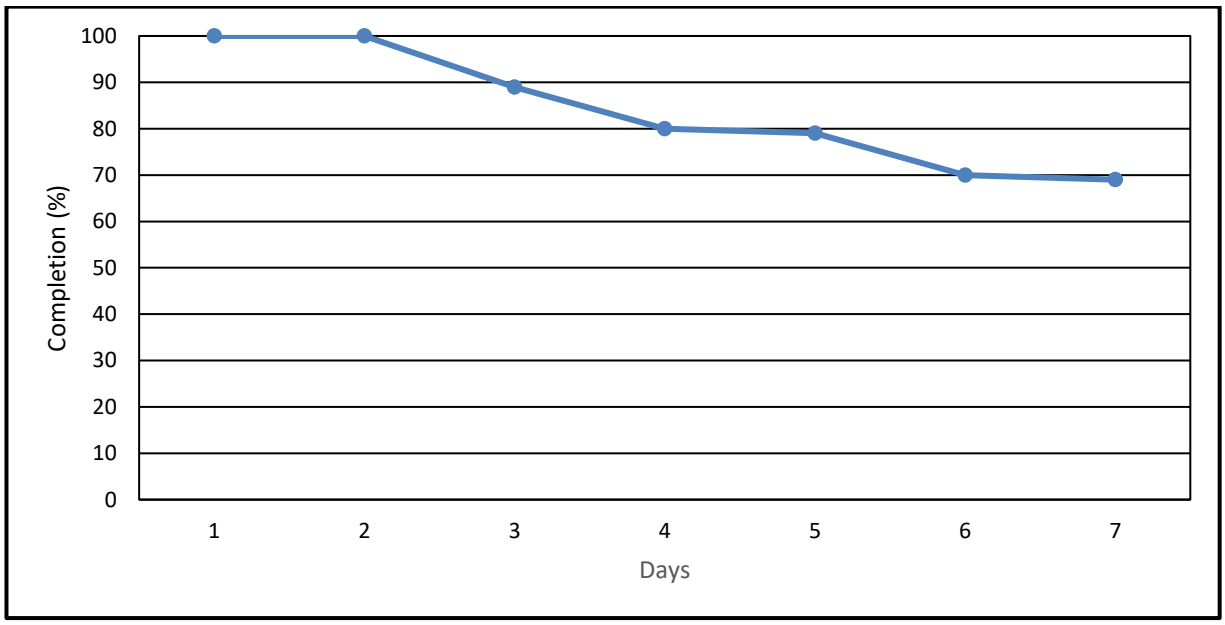

Figure 16 Experience sampling methodology completion rates (N=6)

4.4 Discussion

This study evaluated the acceptability and feasibility of ESM and passive remote monitoring in a forensic mental health setting. A secondary aim was to investigate differences in acceptability and feasibility between the two passive remote monitoring devices presented

in the staff focus groups in Chapter 4. It was anticipated that the findings of this study would inform the decision of what device to use in the later studies reported in this thesis.

Both staff and service users considered passive remote monitoring to be acceptable, based on high acceptability ratings in the user-experience questionnaire. Findings from these questionnaires indicated relatively few statistically significant differences between the two devices, though battery life and integration with users' daily routine emerged as significantly better in the Empatica E4 compared to the Biovotion Everion. Further inspection of the technical logs provided to participants as part of the study indicated that two participants (both using the Biovotion Everion) encountered technical difficulties with the device. Post-study investigation of these technical issues (random vibration of the device) suggested that these occurred as a result of a loss of contact between the device and users' skin, prompting a vibrating alert from the device and rendering any data collected during this period unusable. These issues, and the potential uncertainty they may cause for participants, suggested the Empatica E4 as a preferable device for the later studies in this thesis.

The suitability of the Empatica E4 was also confirmed following analysis of the device usage over the study and quality of data acquired by both devices. Staff and service users recorded an acceptable level of data throughout the study, and, as anticipated, a proportion of these data were identified as artefacts. The Empatica E4 demonstrated a significantly lower proportion of artefacts and was therefore considered optimal for future studies.

Service users also considered the ESM procedure to be acceptable and importantly reported that engaging in this exercise did not impede their ability to carry out their usual daily activities. This was an important consideration to ensure that participation would not have a detrimental effect on their daily routine. Engagement with the ESM procedure was also positive and demonstrated anticipated reductions as the study progressed as reported in previous research (Edwards et al., 2018).

4.4.1 Strengths, Limitations and Future Research

Service users are admitted and discharged from the recruitment site in this study at a relatively low frequency, as in most forensic mental health settings. As recruitment was also planned for future studies in this thesis (reported in Chapters 6, 7 and 8) this limited the number of potential participants who were available to take part in this pilot study. This may therefore limit the identification of relevant acceptability issues and generalisability to a larger sample of service users. The ward approached for participation was specifically chosen

as it provided care for service users of various ages, risk levels and at different stages of their care pathway, but future pilot studies of novel remote monitoring approaches would be optimised with larger samples.

Acceptability and adherence of to both the ESM and passive remote monitoring procedure was good and was a necessary precondition for the later studies planned in this thesis. However, it is unclear how this may change over longer periods of time, with the data reported in this study indicating a decline in acceptability and adherence towards the end of the study. This has implications for whether remote monitoring may represent a short- or long-term strategy for monitoring risk of aggression and could be a focus for future research.

While service users participated in a repeated measures design and provided data across both passive remote monitoring device, this design was not considered feasible for staff participants. Requiring staff to evaluate two devices in addition to their clinical duties was considered too burdensome, reflecting some of the issues raised in the staff focus groups in Chapter 3. Devices were therefore randomly allocated to avoid potential bias, but future research could benefit from repeated measures evaluation of devices.

4.5 Chapter Conclusion

This study investigated the acceptability and feasibility of ESM and passive remote monitoring procedures among a sample of forensic mental health staff and service users. Acceptability of remote monitoring is a key barrier to engagement, and it was essential to investigate this and highlight potential usability issues before progressing to the later studies reported in this thesis. Both ESM and passive remote monitoring were considered acceptable and feasible based on participant self-report and objective indices of device usage and data quality. A secondary aim was to compare the acceptability and feasibility of the Empatica E4 and Biovotion Everion, to select the optimal device to take forward in the future studies. Based on the findings the Empatica E4 was selected as the optimal device for use in future studies.

Chapter 5 : Identifying Recording Periods to Capture Psychophysiological Change

The work presented in this chapter is currently under review for publication:

Greer, B., Chelliah, A., Cella, M., & Wykes, T. Using remote monitoring of shift-related stress in forensic mental health staff: Feasibility, acceptability and validity. *Journal of Psychiatric and Mental Health Nursing.*

5.1 Introduction

Chapter 4 confirmed that passive remote monitoring technology is feasible and acceptable to forensic mental health staff and service users, which is a vital consideration for later studies in this thesis and any potential use of this technology in healthcare services in the future. An equally important consideration is whether this technology is sensitive to variability in psychophysiological parameters, specifically whether it is able to detect meaningful change in these parameters (Düking et al., 2018). One way to evaluate this is through experimental techniques to induce change in psychophysiological arousal, such as visual/auditory stimuli (Siedlecka & Denson, 2019). Alternatively, a more ecologically valid approach is to examine naturally occurring variability in response to environmental stressors. One such group of individuals likely to show frequent variability in psychophysiological arousal is healthcare staff.

Sources of workplace stress in healthcare settings are varied and include long-term stressors such as workload and resource limitations (McTiernan & McDonald, 2015), as well as episodic stressors such as exposure to violence and aggression (Foster et al., 2020; Johnson et al., 2018). Research with nurses in physical healthcare settings has identified variability in psychophysiological arousal. For example, studies have reported decreased HRV among rotating shift versus permanent shift staff (Burch et al., 2019; Lecca et al., 2019). Järvelin-Pasanen et al. (2013) and Goffeng et al. (2018) have also reported significant differences in HRV parameters between work shifts and leisure or rest time. Little is known about these fluctuations in psychophysiological arousal in forensic mental health care, with one study reporting that increased electrodermal activity in a forensic mental health staff sample was significantly associated with symptoms of burnout (de Looff et al., 2019). Forensic mental health services are characterised by high levels of stress (Brown et al., 2017; Dickinson & Wright, 2008) and aggression (Renwick et al., 2016), therefore frequent fluctuations in psychophysiological arousal may be expected. This sample may therefore provide an

opportunity to evaluate the sensitivity of passive remote monitoring technology to psychophysiological arousal in response to real-life stressors.

In addition to evaluating the sensitivity of passive remote monitoring devices, continuous psychophysiological assessments among forensic mental health staff could help to identify situations where stress increases. Workplace stress experienced by healthcare staff contributes to recruitment and retention challenges and negative physical and psychological health outcomes (Royal College of Nursing, 2013; Ward, 2011)**,** but there are currently few ways of measuring these episodic changes which may be relevant to overall well-being. A higher observed HRV, for example, could be considered advantageous as the ability to quickly increase heartbeat may enable the individual to quickly adapt to an acute stressful situation. Conversely, a lower HRV, reflecting a slower variation in heartbeat, could inhibit an individual's ability to quickly respond to a stressor at a psychophysiological level.

This study investigates whether passive remote monitoring can identify changes in psychophysiological stress, by comparing differences in EDA and HRV among a sample of forensic mental health staff when on- compared to off- shift. It was hypothesised that participants would show significantly greater EDA and reduced HRV when on-shift, compared to off-shift. These shift periods were further analysed according to 20-, 40-, and 60-minute epochs, to explore specific timeframes where significant differences in psychophysiological stress could be identified. Shorter time periods may capture short-lived peaks in psychophysiological stress, while longer time periods may reflect individuals' recovery from these peaks.

5.2 Method

5.2.1 Ethical Approval

Ethical approval was obtained from the Wales Research Ethics Committee 5 (ref: 18/WA/0219) on 18th October 2018 and Health Research Authority on 23rd October 2018. Research and Development approval was granted by South London and Maudsley NHS Foundation Trust (ref: R&D2018/078) on 6th November 2018.

5.2.2 Participants

Participants were staff in a medium-secure forensic mental health service in South London, UK. Staff were eligible to participate if their role involved direct contact with patients. All five wards in this service were approached and consented to take part.

5.2.3 Measures

5.2.3.1 Psychophysiology

The Empatica E4 (Empatica Srl, Milan, Italy), worn around participants' left wrist, provided a measure of EDA at a sampling frequency of 4 Hz. Interbeat intervals (RR intervals) were used to calculate HRV measured through a photoplethysmography sensor with a sampling frequency of 64 Hz. RR intervals represent the time in milliseconds between successive heartbeats, specifically the R wave of the cardiac QRS complex, while HRV represents a measure of the variation in time between successive heartbeats. As physical motion can affect psychophysiological parameters, we recorded it through a 3-axis accelerometer with a sampling frequency of 32 Hz. Motion was controlled for in all statistical analyses.

5.2.4 Procedure

Following informed consent, participants were provided with comprehensive instructions for operating the E4. They were asked to wear the device each day during their normal waking hours for seven consecutive days, taking it off only to bathe and sleep and to keep the device charged. During the study, participants were contacted in-person or by telephone at least once to ensure adherence to the protocol and address any issues. This study was conducted and reported following Guidelines for Reporting on Articles on Psychiatry and Heart Rate Variability (Appendix 4; Quintana et al., 2016) and reporting guidelines for electrodermal activity measurements (Appendix 5; Boucsein et al., 2012).

5.2.5 Data Pre-Processing

The first five minutes from each recording file was excluded to allow blood vessels in the wrist time to adapt to compression from the E4's sensors (Taylor et al., 2015). Recordings for each day of participation were segmented into 20- 40- and 60-minute epochs using an automated script written in Python and categorised as on- or off-shift. All participants had at least one day meeting this criterion. To reduce the risk of sampling bias, data were resampled 1,000 times and 10 random samples of on-shift and off-shift recordings were extracted for all participants for each day of participation. Aggregate results for these random samples were then calculated and reported below.

Raw EDA data were passed through a median filter (window size 44) as this type of signal filter is particularly well-suited to identify and remove rapid frequency spikes (see **Figure 17**). Data were then passed through a Butterworth low-pass filter (order = 5; lower cut-off frequency = 0.5) using the MATLAB Ledalab package. This second filter was applied as

following removal of rapid frequency spikes through the median filter, high frequency noise typically remains (see **Figure 18**). Interbeat intervals were pre-processed using Kubios using its automatic artefact detection algorithm (Lipponen & Tarvainen, 2019). An index of overall movement for each epoch was calculated from the actigraphy sensor by the standard Euclidean metric (Cella et al., 2018).

5.2.6 Analysis

Phasic and tonic components of the EDA signal were extracted through continuous decomposition analysis (Benedek & Kaernbach, 2010a, 2010b). This method offers two key advantages over traditional trough-to-peak analysis. First, continuous decomposition analysis enables the phasic and tonic components of the EDA amplitude to be partitioned. Second, tradition trough-to-peal analysis can overestimate EDA amplitudes due to rapid successive skin conductance responses (SCR), as illustrated in **Figure 19** and **Figure 20**. Heart rate variability was calculated based on the mean of interbeat intervals (mean RR), standard deviation of normal-to-normal interbeat intervals (SDNN), as this measure demonstrates greater accuracy over sampling periods shorter than one hour (Cella et al., 2019), and root mean square of successive differences (RMSSD).

Kolmogorov-Smirnov tests were conducted to explore whether the data were normally distributed, and the data were log-transformation before analysis if not. Strong intercorrelations are expected among psychophysiological parameters, as they are components of the same branch of the autonomic nervous system. These parameters and PPG assessment are sensitive to physical motion (Maeda et al., 2011). Pearson R or Spearman rho correlation coefficients were therefore conducted to assess the relationship between all psychophysiological parameters and motion, to assess the validity of these parameters and impact of physical motion. Differences in HRV between on- versus off-shift were investigated using repeated measures ANOVAs, with any statistically significant differences then investigated further by considering whether the effects persisted after controlling for age, number of years in post, and physical motion. EDA data were not normally distributed after log transformation and were therefore assessed using Friedman tests. All analyses employed a significance threshold of $p < 0.05$ and were conducted using SPSS v.25.

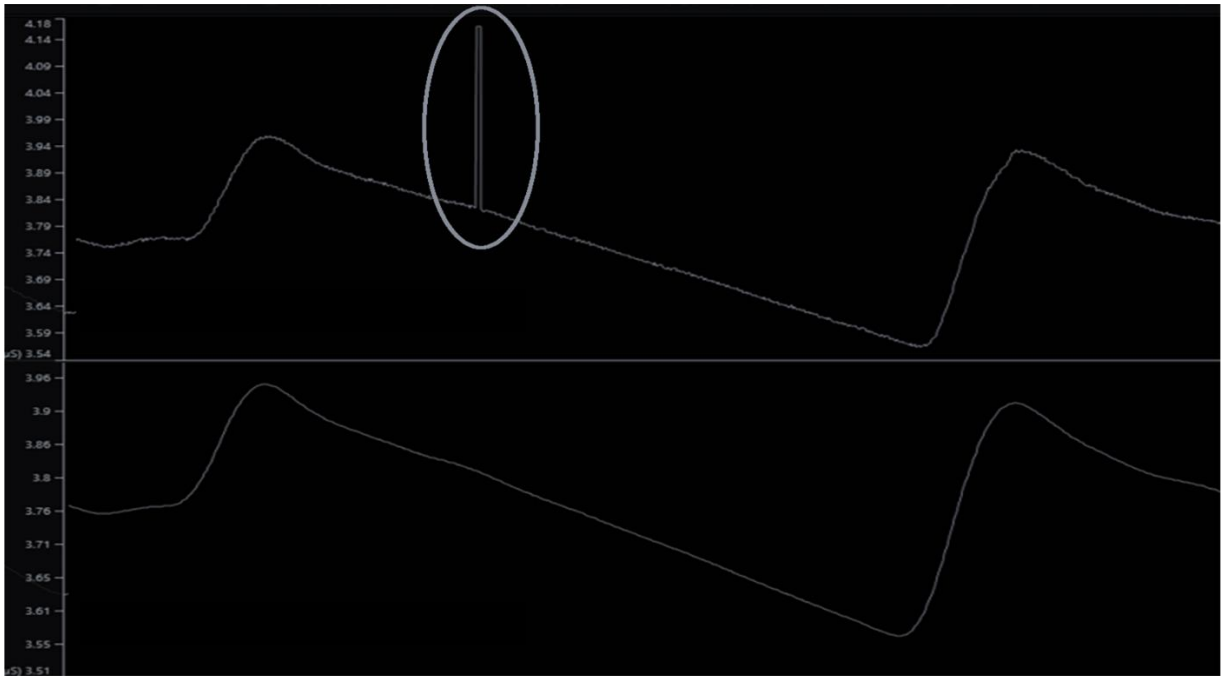

Figure 17 Rapid artefact (top) and removal through a median filter (bottom)

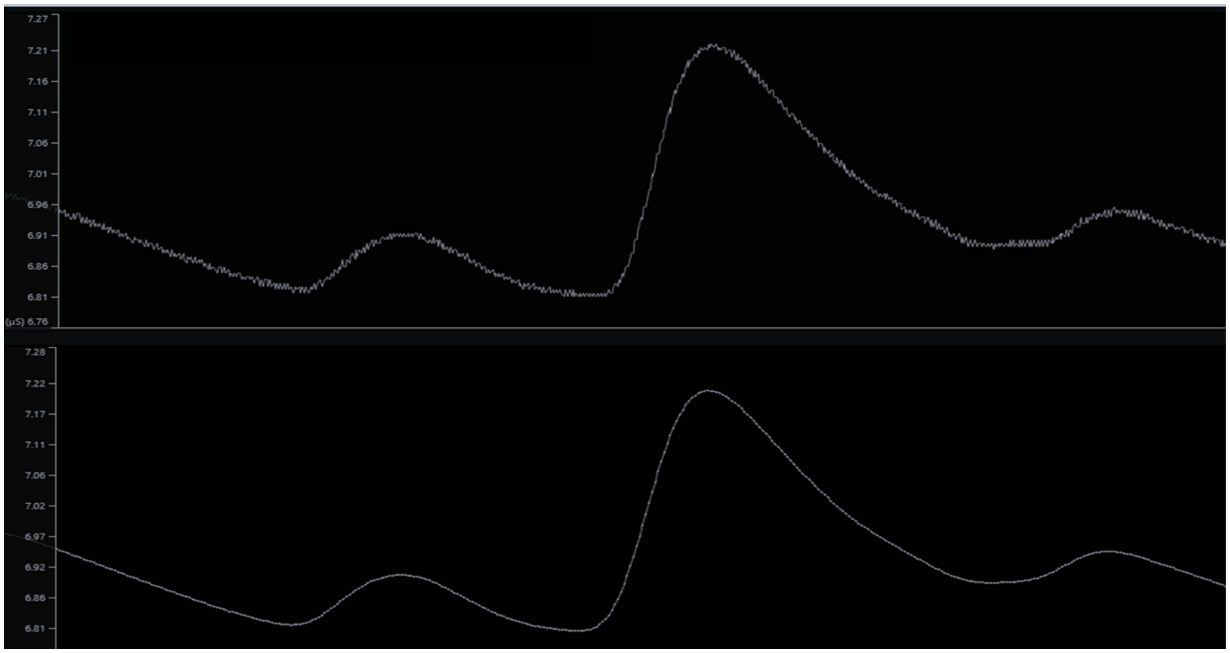

Figure 18 Example of high-frequency noise (top) and removal through a low-pass filter (bottom)

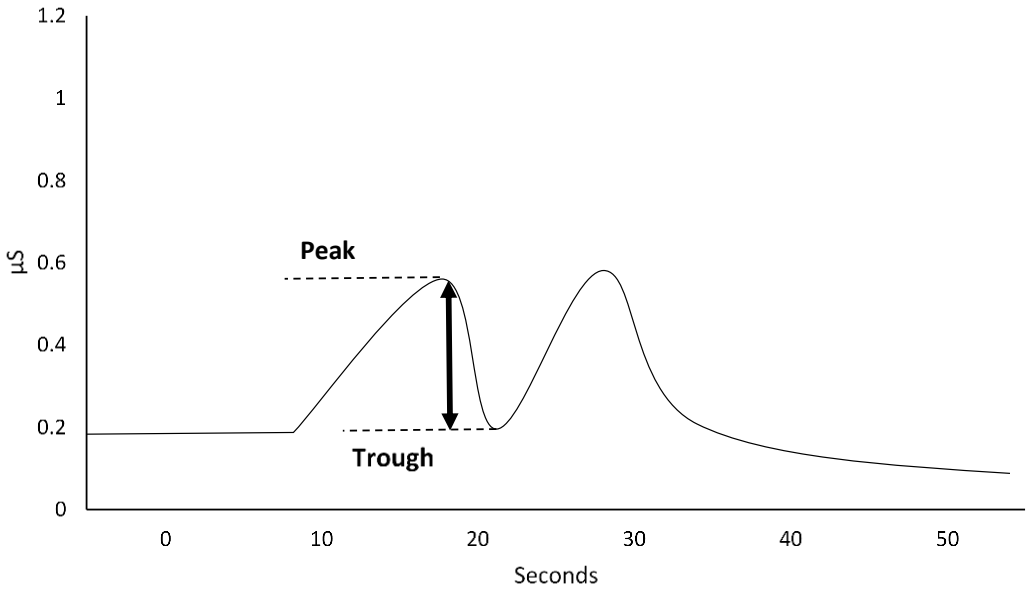

Figure 19 Trough to peak analysis

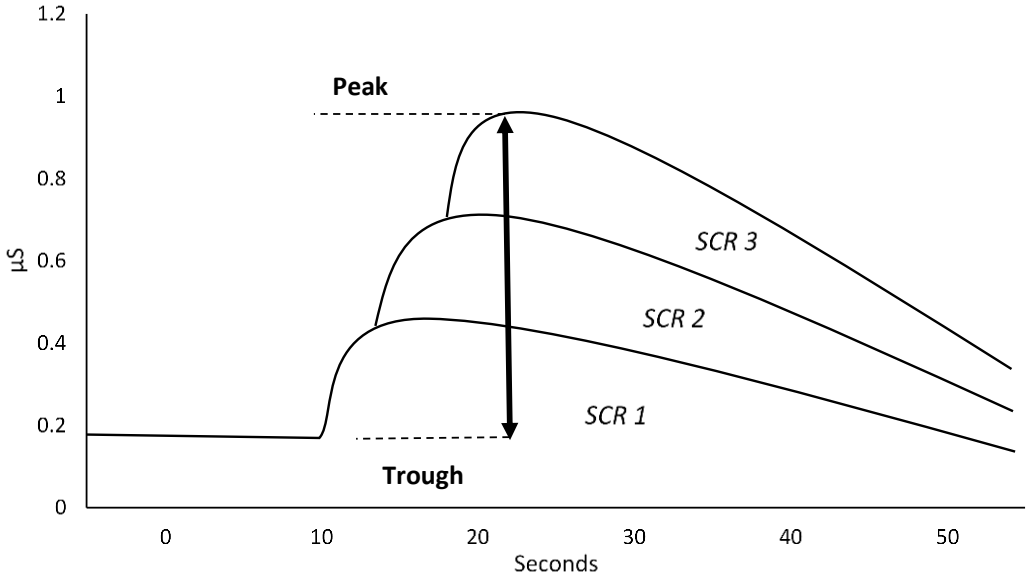

Figure 20 Overestimation of amplitude due to successive skin conductance responses

5.3 Results

Thirty staff were approached and 18 consented to participate (11 women, 7 men). Those who declined reported not wanting to wear the device during working hours (*n* = 3) or did not specify a reason (*n* = 9). Participant demographics are reported in

Table 9. There were 91 working and 44 non-working days across the sample and 1,081 complete hours of recording data were obtained.

Table 9 Participant demographics

Characteristics	Total (N = 18)
Age (years)	
Mean (SD)	40.3 (10.8)
Range	25 – 59
Ethnicity	
Black African	13
White British	2
Black Caribbean	1
Other White Background	1
Other Asian Background	1
Job role	
Staff Nurse	13
Ward Manager	2
Occupational Therapist	2
Care Support Worker	1
Years in post	
Mean (SD)	5.8 (3.8)
Range	1-15

5.3.1 Relationship Between Variables

Table 10 illustrates the correlations between psychophysiological variables. As expected, EDA and HRV variables demonstrated statistically significant intercorrelations across all epochs. These variables were not consistently correlated with each other or movement across epochs.

5.3.2 Group Differences

For 20-minute epochs participants had significantly greater phasic activity ($\chi^2(1) = 45.496$, $p < .001$) and tonic activity ($\chi^2(1) = 22.797$, $p < .001$) when on-shift. These differences in phasic activity were significant in post hoc analyses with Wilcoxon signed-rank tests with a Bonferroni correction applied ($Z = -5.741$, $p < .001$), but were not significant for tonic ($Z = -.708$, $p = .479$) activity (see **Figure 21**). Statistically significant differences in the same

direction were also identified for SDNN (F(1,57) = 4.309, p = .042, η_p^2 = .070), which remained significant after controlling for participant age (F(1,56) = 3.285, p = .036, η_p^2 = .042), years-in-post (F(1,56) = 2.478, p = .026, η_p^2 = .038), and movement (F(1,56) = 4.126, p = .047, η_p^2 = .062), but not RMSSD (F(1,57) = 3.267, p = .081) or mean RR (F(1,57) = 4.101, p = .051) (see **Figure 22**).

For 40-minute epochs, participants had significantly greater phasic activity ($\chi2(1) = 13.227$, p = .004) when on- versus off-shift, but not tonic activity ($\chi2(1) = 3.099$, p = .074). These differences in phasic activity were significant in post hoc analyses with Wilcoxon signed-rank tests with a Bonferroni correction applied (Z = -2.288, p = .022). (see Figure 1). Statistically significant differences in the same direction were also identified for SDNN (F(1,57) = 4.591, p = .037, η_p^2 = .081), which remained significant after controlling for participant age (F(1,56) = 2.58, p = .015, η_p^2 = .054), years-in-post (F(1,56) = 1.513, p = .048, η_p^2 = .061), but not movement (F(1,56) = .709, p = .40). No statistically significant differences were identified for RMSSD (F(1,57) = 1.01, p = .308) or mean RR (F(1,57) = 1.210, p = .297).

For 60-minute epochs there were no statistically significant differences in EDA (phasic: $\chi2(1) = .310$, p = .564; tonic: $\chi2(1) = .201$, p = .908) or HRV variables (SDNN: F(1,48) = 0.310, p = .545; RMSSD: F(1,48) = 1.222, p = .274; mean RR: F(1,48) = .570, p = .454) between participants when on- versus off-shift.

Table 10 Correlations between variables

	20-Minutes						40-Minutes						60-Minutes					
	Phasic	**Tonic**	**Mean_ RR**	**SDNN**	**RMSSD**	**Motion**	**Phasic**	**Tonic**	**Mean_ RR**	**SDNN**	**RMSSD**	**Motion**	**Phasic**	**Tonic**	**Mean_ RR**	**SDNN**	**RMSSD**	**Motion**
Phasic	-	*r* = .71 *p* <.001	*r* =-.05 *p* = .601	*r* = .13 *p* = .170	*r* =.05 *p* = .607	*r* = .26 *p* = .005	-	*r* = .53 *p* <.001	*r* =-.05 *p* = .581	*r* = .10 *p* = .310	*r* = .002 *p* = .982	*r* = .27 *p* = .006	-	*r* = .76 *p* <.001	*r* = .13 *p* = .211	*r* = .24 *p* = .018	*r* = .16 *p* = .128	*r* = .49 *p* <.001
Tonic	*r* = .71 *p* <.001	-	*r* = .20 *p* = .028	*r* = .14 *p* = .140	*r* = .06 *p* = .505	*r* = .29 *p* <.001	*r* = .53 *p* <.001	-	*r* = .06 *p* = .552	*r* = .17 *p* = .077	*r* = .04 *p* = 681	*r* = .08 *p* = .410	*r* = .76 *p* <.001	-	*r* = .22 *p* = .030	*r* = .32 *p* <.001	*r* = .22 *p* = .028	*r* = .33 *p* <.001
Mean_RR	*r* =-.05 *p* = .601	*r* = .20 *p* = .028	-	*r* = .58 *p* <.001	*r* = .58 *p* <.001	*r* = .15 *p* = .096	*r* =-.05 *p* = .581	*r* = .06 *p* = .552	-	*r* = .61 *p* <.001	*r* = .65 *p* <.001	*r* = .12 *p* = .207	*r* = .13 *p* = .211	*r* = .22 *p* = .030	-	*r* = .76 *p* <.001	*r* = .74 *p* <.001	*r* = .23 *p* = .023
SDNN	*r* = .13 *p* = .170	*r* = .14 *p* = .140	*r* = .58 *p* <.001	-	*r* = .96 *p* <.001	*r* = .29 *p* < .001	*r* = .10 *p* = .310	*r* = .17 *p* = .077	*r* = .61 *p* <.001	-	*r* = .94 *p* <.001	*r* = .35 *p* <.001	*r* = .24 *p* = .015	*r* = .32 *p* <.001	*r* = .76 *p* <.001	-	*r* = .96 *p* <.001	*r* = .35 *p* <.001
RMSSD	*r* =.05 *p* = .607	*r* = .06 *p* = .505	*r* = .58 *p* <.001	*r* = .96 *p* <.001	-	*r* = .24 *p* = .008	*r* = .002 *p* = .982	*r* = .04 *p* = 681	*r* = .65 *p* <.001	*r* = .94 *p* <.001	-	*r* = .35 *p* <.001	*r* = .16 *p* = .128	*r* = .22 *p* = .028	*r* = .74 *p* <.001	*r* = .96 *p* <.001	-	*r* = .34 *p* <.001
Motion	*r* = .26 *p* = .005	*r* = .29 *p* <.001	*r* = .15 *p* = .096	*r* = .29 *p* < .001	*r* = .24 *p* = .008	-	*r* = .27 *p* = .006	*r* = .08 *p* = .410	*r* = .12 *p* = .207	*r* = .35 *p* <.001	*r* = .35 *p* <.001	-	*r* = .49 *p* <.001	*r* = .33 *p* <.001	*r* = .23 *p* = .023	*r* = .35 *p* <.001	*r* = .34 *p* <.001	-

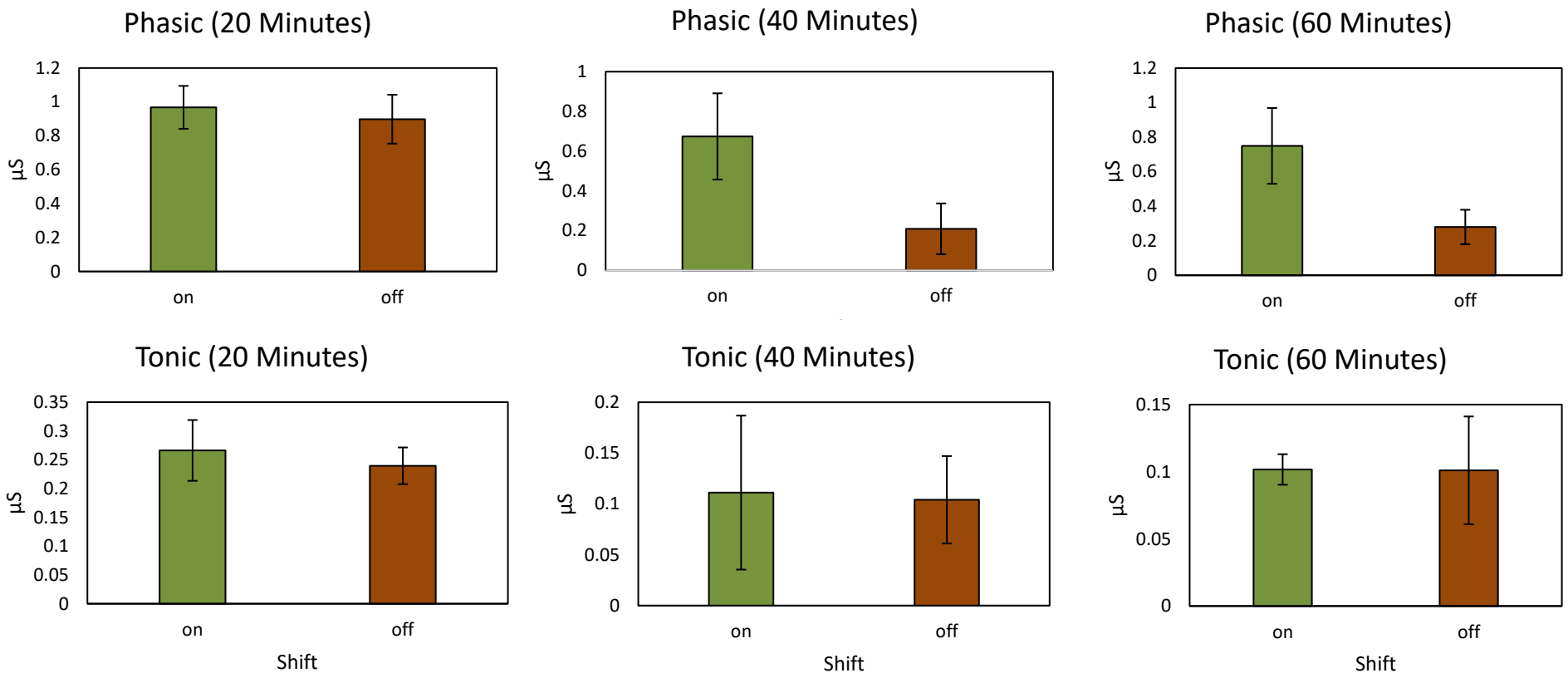

Figure 21 Electrodermal activity values (error bars reflect SD)

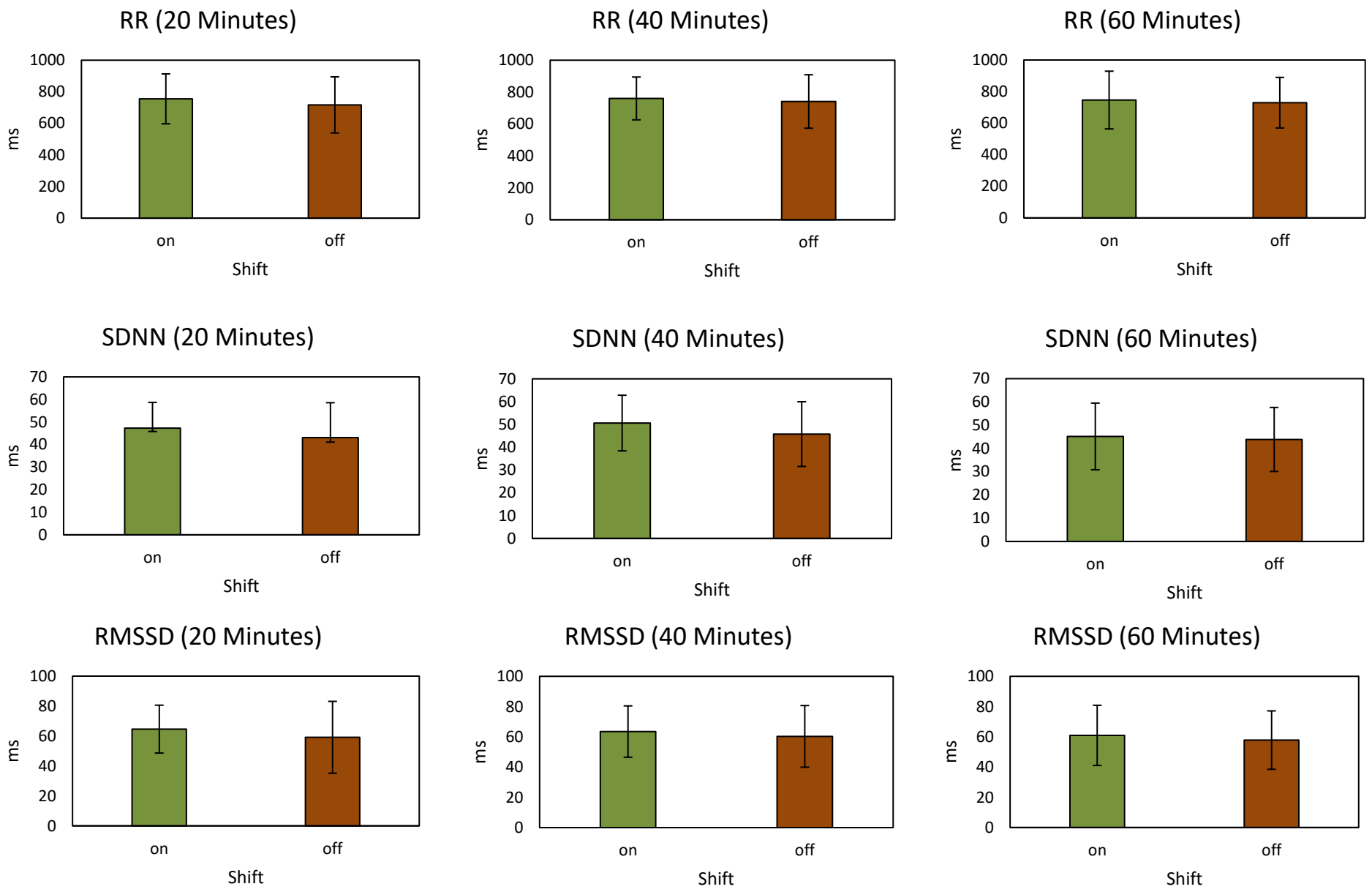

Figure 22 Heart rate variability values (error bars reflect SD)

5.4 Discussion

This study compared on- and off-shift differences in psychophysiological stress, as measured in real-time, among forensic mental staff. As hypothesised, statistically significant differences in phasic EDA were identified between on- and off-shift periods, when analysed in 20- and 40-minute epochs. Statistically significant differences were also identified in SDNN when analysed in 20- and 40-minute epochs, though the latter was not significant after controlling for movement. Longer recording periods capture more instances of heightened physical activity than shorter recording periods, which may be why movement had a greater effect on data from the 40- versus 20-minute epochs. The direction of these significant findings indicated that participants experienced significantly greater activity in the SNS and PNS while they were on shift compared to while they were not on shift.

The significant on-shift reductions in HRV reported in this study are consistent with those identified in previous research conducted among physical healthcare staff (Goffeng et al., 2018; Järvelin-Pasanen et al., 2013). Within the neurovisceral integration model (Thayer & Lane, 2000), HRV plays a fundamental role in ensuring an individual's flexibility to adapt to changing environmental, psychological, and behavioural stimuli. Lower HRV can reflect difficulties with inhibiting cognitive, affective, and behavioural responses (e.g. worry and vigilance; Chalmers et al., 2014). These findings suggest that participants demonstrated a reduced adaptability during on-shift periods, possibly as a result of heightened stress during these periods relative to off-shift periods. Consistent with the HRV findings, the significant increases in EDA during on-shift periods suggests participants were experiencing significantly greater emotional arousal compared to off-shift periods. Specifically, on-shift periods were characterised by heightened short-term stimulus-specific responses (phasic activity; Boucsein, 1992).

Analysis of participants' data in relation to different time epochs has not been carried out before. The variability of statistically significant findings across the three epochs suggests greater temporal accuracy at shorter recording periods (in the range of 20- to 40-minutes) compared to longer epochs. The greater temporal accuracy afforded by shorter recording periods could enable changes in psychophysiological arousal to be linked to specific events occurring in the individuals' environment (e.g. interactions with service users and staff, and behavioural incidents on the ward). Passive remote monitoring technology could therefore provide a more accurate understanding of the specific sources of stress in the work environment (Jovanov et al., 2011), which may differ between staff members. This study

aimed to identify optimal periods for identifying change in psychophysiological arousal but not to identify the specific source(s) of this change in participants' environment. Participants in future research could be provided recording instructions to identify factors and events in their environments which might be linked to their psychophysiological changes. This understanding could therefore inform individualised approaches for supporting staff to manage stress.

Contrary to our hypothesis, no statistically significant differences were identified for mean RR intervals or RMSSD when analysed in any epoch. In addition, no statistically significant differences were identified for any EDA or HRV values when analysed in 60-minute epochs. A higher noise-to-signal ratio over longer time periods may account for some of these statistically non-significant findings. For example, analysis of SDNN may demonstrate reduced accuracy over longer recording periods (Shaffer & Ginsberg, 2017). The findings for 60-minute epochs may also reflect psychophysiological recovery following specific events occurring in the recording period, which might not be captured in shorter recording periods. The shorter recording periods may therefore be better suited to identifying short-lived peaks in psychophysiological stress, with longer recording periods able to reflect overall recovery from these peaks.

The non-significant findings reported could also reflect staff members' adaptive reaction to a stressful working environment, as suggested previously (Sedgwick et al., 2017). For example, using an affective startle paradigm Loomans et al. (2015) reported a diminished startle response to aversive images among forensic mental health staff and service users compared to community controls. Individuals working in these environments could therefore demonstrate attenuated responses to stressors, accounting for the lack of significant differences identified between shift categories.

5.4.1 Strengths, Limitations and Future Research

To our knowledge, this is the first study using pRMT among healthcare staff to investigate both EDA and HRV. Previous research has typically focussed exclusively on HRV and this study's findings in relation to EDA represent a novel contribution to the role played by both the sympathetic and parasympathetic branches of the ANS in staff psychophysiological stress.

The length of recording (seven consecutive days) was greater than previous research, which ranged from 24-96 hours. While this provided a rich source of ecologically valid data, care

was taken not to impose significant workload burdens on participants during this time. This limited the opportunity to collect additional relevant data which could have an impact on the observed data (e.g. state stress/anxiety, participants' activities when on- and off-shift). Future research could implement a blended passive and active remote monitoring approach, in which assessments of thoughts, mood, and behaviour are collected through brief smartphone-delivered questionnaires. This approach was not considered feasible for this study due to the secure setting where mobile phones were not permitted.

5.5 Chapter Conclusion

This study identified significant differences in psychophysiological arousal between on- versus off-shift periods among forensic mental health staff. Across 20- and 40-minute epochs, participants demonstrated significantly heightened EDA and reduced HRV when on-shift compared to off-shift, while analysis of 60-minute epochs did not identify any statistically significant differences. These findings indicate that the passive remote monitoring device was sensitive to variability in psychophysiological arousal over these shorter epochs, and this informed the analysis strategies in Chapters 6, 7 and 8. Beyond the impact on this thesis, this study also has potential implications for managing wellbeing among forensic mental health service staff. Passive remote monitoring devices could be used to link changes in arousal to specific situations in the work environment, as they are more closely related to events than longer recording periods. This could subsequently be used to inform individualised approaches to supporting staff to manage these sources of stress.

Chapter 6 : Does Short-Term Change in Dynamic Risk Factors Predict Imminent Inpatient Aggression? An Experience Sampling Methodology Study

6.1 Introduction

Inpatient forensic mental health services experience high levels of aggression (Renwick et al., 2016), with negative consequences for both service users and staff. Up to 60% of service users in forensic mental health services are diagnosed with a schizophrenia-spectrum condition (de Tribolet-Hardy & Habermeyer, 2016) and dynamic risk factors are reported to be a significant contributor to hospitalisation in this group (Morgan et al., 2016). Change in dynamic risk factors (e.g. affect and peer relationships; Heffernan & Ward, 2017) may also predict aggression within inpatient services and are therefore integral to models of rehabilitation, such as the RNR and GLM models (Ward, 2016; Ward & Willis, 2016).

Dynamic risk factors have been shown to change during inpatient treatment (Heffernan et al., 2019), with change measured over the course of weeks (Clarke et al., 2017) and months (De Vries Robbe et al., 2015). However, there is little empirical evidence establishing the degree of short-term change (e.g. minutes and hours) in these risk factors (Abidin et al., 2013a). This is because of the complexity of assessing information frequently in forensic settings with informant-report scales. Infrequent assessments are ill-equipped to capture episodic and potentially rapid changes in factors such as mood which have shown substantial within-person variability and associations with aggression escalation (Kiekens et al., 2020).

Experience Sampling Methodology (ESM) is a structured diary method assessing momentary thoughts, feelings and behaviours (Myin-Germeys et al., 2009), and offers an opportunity to measure change over short periods without increasing staff assessment burden. ESM has been implemented in various mental health populations and settings (Cella et al., 2019; Edwards et al., 2016; Verhagen et al., 2016a), including previous studies in forensic settings (Humber et al., 2013). The repeated momentary assessments of ESM are less susceptible to recall bias and enable longitudinal variability in responses to be investigated. Experience Sampling Methodology could therefore illustrate how dynamic risk factors vary over short periods, and how these changes relate to subsequent aggressive behaviour.

Identifying the extent to which dynamic risk factors change over short periods, and whether this change is associated with aggression, could enable more timely support to be offered to service users that is targeted at the specific factors driving their behaviour. This study uses ESM in an inpatient forensic mental health service to achieve two main aims. The first is to investigate the degree of short-term change in individual ESM items over time within individuals and could be potential aggression indicators. We expect within-participant variability would be observed at both the day- and ESM prompt-level. The second aim is to investigate whether these changes predict aggression and could therefore be used to accurately monitor aggression risk.

6.2 Method

6.2.1 Ethical Approval

Ethical approval was granted by the Wales Research Ethics Committee 5 (ref: 18/WA/0219) on 18th October 2018 and Health Research Authority on 23rd October 2018. Research and Development approval was granted by South London and Maudsley NHS Foundation Trust (ref: R&D2018/078) on 6th November 2018.

6.2.2 Power Calculation

An *a priori* power calculation based on a linear multiple regression model with a random factor was performed to estimate the required sample size for this study and those reported in Chapters 7 and 8. A total sample of 30 would be required to detect a multiple correlation coefficient of 0.4 with an inter-correlation of ≥0.5, but this does not account for the clustering of data which occurs with ESM. The target sample size was increased to 40, in line with previous research (Edwards et al., 2018; Kimhy et al., 2012) and to account for the potential high level of inter-correlation.

6.2.3 Participants

Participants were service users in a male medium-secure forensic mental health service in South London, UK. Service users were eligible to participate if they possessed capacity to consent and if participation would not disrupt their care. These eligibility criteria were determined by participants' Responsible Clinician.

6.2.4 Measures

6.2.4.1 Contextual clinical and demographic characteristics

Demographics (age and ethnicity), current diagnosis (ICD-10), length of treatment within the service and current antipsychotic medications (converted to chlorpromazine equivalents;

Woods, 2003) were extracted from participants' electronic hospital records. In addition, the following clinical characterisation measures were used:

Psychopathy: Psychopathy Checklist-Revised; PCL-R (Hare, 1991) is a 20-item scale of psychopathy, a trait with significant associations with aggression and antisocial behaviour (Leistico et al., 2008), completed by trained raters within the service.

Symptom Severity: Brief Psychiatric Rating Scale; BPRS (Overall & Gorham, 1962) is a 24-item scale based on participant self-report and observed behaviour and speech, with ratings based on the previous two weeks.

6.2.4.2 Experience Sampling Methodology

The ESM procedure for this study was the same as that previously outlined in the pilot study in Chapter 4.

6.2.4.3 Aggressive Behaviour: *Modified Overt Aggressive Scale;* MOAS *(*Alderman, Knight, & Morgan, 1997)

The MOAS was used to record the occurrence of four categories of aggression occurring during the study: physical aggression against others, verbal aggression, aggression against property, and aggression against self (Autoaggression). Ratings were completed for every 24-hour period for each participant by a member of the nursing team. Aggressive incidents recorded in each participants' hospital records were also recorded and cross-referenced with the MOAS ratings, to ensure the frequency of incidents was accurately captured.

6.2.5 Procedure

Following informed consent, comprehensive instructions on how to complete the ESM procedure were provided. For ESM questions a time-contingent design with a random sampling schedule was used (Myin-Germeys et al., 2018). Prompts were separated by at least 45 minutes and were scheduled to occur during participants' typical waking hours. Each prompt signalled the participant to complete one page of questions in their ESM booklet. Participants were asked not to retrospectively complete pages if they missed a prompt. The researcher met with each participant at least three times over the course of the week to collect completed ESM booklets and address any questions.

6.2.6 Analysis

STATA 16 was used for all analyses (StataCorp, 2019) and statistical significance was set at $p < .05$. Chi-square tests and ANOVAs were used to explore whether demographic and clinical characteristics differed according to diagnosis and between participants who had exhibited

aggression during the study versus those who had not. Multiple imputation was used to handle missing ESM responses and participants who had responded to less than 20% of prompts were excluded from the analyses (Oorschot et al., 2013). Analysis was conducted in three stages.

i) Within-participant variation

Within-participant variability was calculated using the XTTABS command. To investigate whether the ESM questions showed sufficient intraindividual change to be considered a dynamic risk factor we adopted a threshold of 50% within-participant variability. Within-participant variability of 100% would indicate that all variability in ESM responses was occurring within-participants over time, while 0% variability would indicate that all variability was occurring between-participants and individual participants' responses were static over time Participants' pattern of responses over the study were then explored using the XTTRANS command, to investigate the magnitude of any changes in participants' responses. Transition probabilities reflect changes in responses between consecutive prompts (e.g. the probability of choosing response option 2 at the second ESM prompt if response option 1 was chosen at the first prompt). This is a measure of the likelihood of participants varying their responses over time.

ii) Factor structure and validity

To reduce the risk of type I errors in the predictive models below, principal components analysis with varimax rotation was conducted to reduce the number of variables entered into the models. Because of the nested structure of the data (ESM prompts nested within participants, nested within days), multilevel Principal Components Analysis was used to partition within- and between-participant variability in ESM responses. Results of the within-participants analysis are presented below.

Multilevel models were conducted using the MIXED command to test the validity of the factor structure. The models accounted for the random (time, day and participant) and fixed effects (the factors) present in the data and were followed up by calculating variance partition coefficients to examine the variance of each factor attributable to the random effects included in the multilevel models (Goldstein et al., 2002). Diagnostic group and presence or absence of aggression were entered into all models to investigate whether the outcome variable differed significantly between these groups.

iii) Relationship with aggression

Multilevel models using the MEPOISSON command were conducted to investigate whether the ESM factors were significantly associated with aggressive behaviour. There were too few

incidents of Autoaggression recorded during the study to construct reliable multilevel models, therefore analysis was limited to physical, verbal and property aggression. These models first assessed the relationship between the outcome and predictor variables at concurrent entry points, to investigate whether participants responses to the ESM questions could predict the occurrence of aggression at any point in the same sampling window. Time-lagged models were then conducted using participants' responses to the ESM questions 20- 40- and 60-minutes prior to the recorded aggressive incident, to investigate whether responses may predict aggression within these time periods. All ESM responses were entered into these models and grouped according to whether i) an aggressive incident was recorded during this ESM prompt window and if so ii) whether this response fell within or outside of the time window. These time periods were informed by previous research (de Looff et al., 2019) chosen as they could afford a practical window of opportunity in the ward-environment to intervene and de-escalate and aggressive incident. Group differences identified in the models outlined above were included as covariates.

6.3 Results

6.3.1 Demographics and Clinical Characteristics

Ninety-seven participants were approached and 41 agreed to participate, 78% had a diagnosis of schizophrenia. Ninety-nine aggressive incidents were reported during the study (Verbal: 75; Physical: 15; Property: 7; Autoaggression: 2) and 1,338 of 2,009 total ESM prompts were completed (66% completion), with no significant differences observed between diagnostic groups or participants with or without recorded aggressive incidents. Participants' demographic and clinical characteristics and differences by diagnostic and aggressive group are presented in **Table 11** and **Table 12**. Participants with a diagnosis of dissocial personality disorder were significantly older, had received treatment within the service for a significantly longer period and were prescribed a significantly lower dose of antipsychotic medication, but did not differ significantly in symptom severity, to participants with a schizophrenia-spectrum diagnosis. Participants with a schizophrenia-spectrum diagnosis were significantly more likely to come from a Black, Asian and Minority Ethnic background.

Table 11 Participant clinical and demographic characteristics

Measure	Total Sample (*N* = 41)	Schizophrenia-Spectrum Condition (*N* = 32)	Dissocial Personality Disorder (*N* = 9)	Group Differences	Direction of Effect
Demographics					
Age; Mean (SD)	39.78 (10.96)	37.16 (10.20)	49.11 (8.46)	F(1,39)=10.31, *p* =.003	DPD>SCZ
Ethnicity (*N*)					
Black British	16	16	0		
White British	15	6	9		
Black Caribbean	5	5	0	$\chi^2(4)=19.99$, *p* =.001	
Black African	3	3	0		
Asian	2	2	0		
Clinical Characteristics					
Treatment Length (Years); Mean (SD)	2.76 (1.74)	2.24 (1.47)	4.58 (1.40)	F(1,39)=18.16, p <.001	DPD>SCZ
Chlorpromazine Equivalent Dosage; Mean (SD)	373.17 (178.92)	434.38 (134.07)	155.56 (148.84)	F(1,39)=29.00, p <.001	SCZ>DPD
PCL-R; Mean (SD)	19.05 (7.32)	17.06 (6.68)	26.11 (4.81)	F(1,39)=14.32, p =.001	DPD>SCZ
BPRS; Mean (SD)	51.83 (12.83)	52.81 (13.24)	48.33 (11.05)	F(1,39)=.858, p =.360	-

Table 12 Demographic and clinical characteristics by presence or absence of aggression

Measure	No-Aggression (*N* = 22)	Aggression (*N* = 19)	Group Differences	Direction of Effect
Demographics				
Age; Mean (SD)	40.68 (10.74)	38.74 (11.40)	F(1,39)=.32, *p* =.557	-
Ethnicity *(N)*				
Black British	7	9	$\chi^2(4)=6.53$, *p* =.163	-
White British	10	5		
Black Caribbean	1	4		
Black African	3	0		
Asian	1	1		
Clinical Characteristics				
Diagnosis *(N)*				
Schizophrenia Spectrum Condition	13	10	$\chi^2(2)=2.18$, *p* =.336	-
Dissocial Personality Disorder	6	3		
Comorbid	3	6		
Treatment Length (Years); Mean (SD)	2.75 (1.95)	2.76 (1.52)	F(1,39)=.001, *p* =.981	-
Chlorpromazine Equivalent Dosage; Mean (SD)	365.91 (172.78)	381.58 (190.18)	F(1,39)=.076, *p* =.784	-
PCL-R; Mean (SD)	18.09 (7.21)	20.16 (7.48)	F(1,39)=.810, *p* =.374	-
BPRS; Mean (SD)	46.95 (11.48)	57.47 (12.14)	F(1,39)=8.12, p =.007	AGG>NAGG

6.3.2 Within-Participant Variation

Measures of central tendency for each ESM question are presented in **Table 13**. Participants' responses range, median and mean, indicating the extent to which their responses were consistent over time, for each ESM question are shown in Appendix 2 . **Figure 23** illustrates the within-participant variability observed for each ESM question. Within-participant variability for all questions exceeded the 50% threshold to be considered a dynamic risk factor. The average within-participant variability across all ESM questions was 70.2%, compared to 29.7% between-participant variability. The greatest difference between within- and between-participant variability was observed in the ESM question relating to relaxation (57.3%), while physical and verbal aggression ideation showed the smallest differences at 15.8% and 14.9% respectively. This suggests that aggressive ideation, while dynamic in nature, did not vary within-participants as much as the other factors studied and was more consistent in its intensity over time. Appendix 3 illustrates the transition probabilities for individual ESM items. The tails of the distributions in Appendix 3 show a general pattern of within-participant variability in responses over time, and a low probability of large changes in response options between consecuitve prompts (i.e. participants were less likely to select response option 7 at the next ESM prompt if they selected response option 1 at the previous prompt, and vice versa).

Table 13 Measures of central tendency for ESM responses

ESM Question	Mean (SD)	Median	Range
Cheerful	4.52 (2.15)	5	1 – 7
Irritated	1.98 (1.52)	1	1 – 7
Angry	1.79 (1.40)	1	1 – 7
Insecure	1.75 (1.34)	1	1 – 7
Others Out to Get Me	1.80 (1.51)	1	1 – 7
Relaxed	4.56 (2.17)	5	1 – 7
Guilty	1.81 (1.62)	1	1 – 7
Confused	1.84 (1.54)	1	1 – 7
Restless	2.14 (1.60)	1	1 – 7
Anxious	2.12 (1.59)	1	1 – 7
Lonely	2.16 (1.79)	1	1 – 7
Satisfied	3.91 (2.45)	4	1 – 7
Don't Want to be Around Others	2.75 (2.16)	2	1 – 7
Down	2.29 (1.93)	1	1 – 7
Good Mental Health	5.57 (1.95)	7	1 – 7
Peer Interaction	4.95 (1.98)	5	1 – 7
Staff Interaction	5.12 (2.01)	6	1 – 7
Physical Aggression Ideation	1.43 (1.10)	1	1 – 7
Verbal Aggression Ideation	1.44 (1.11)	1	1 – 7

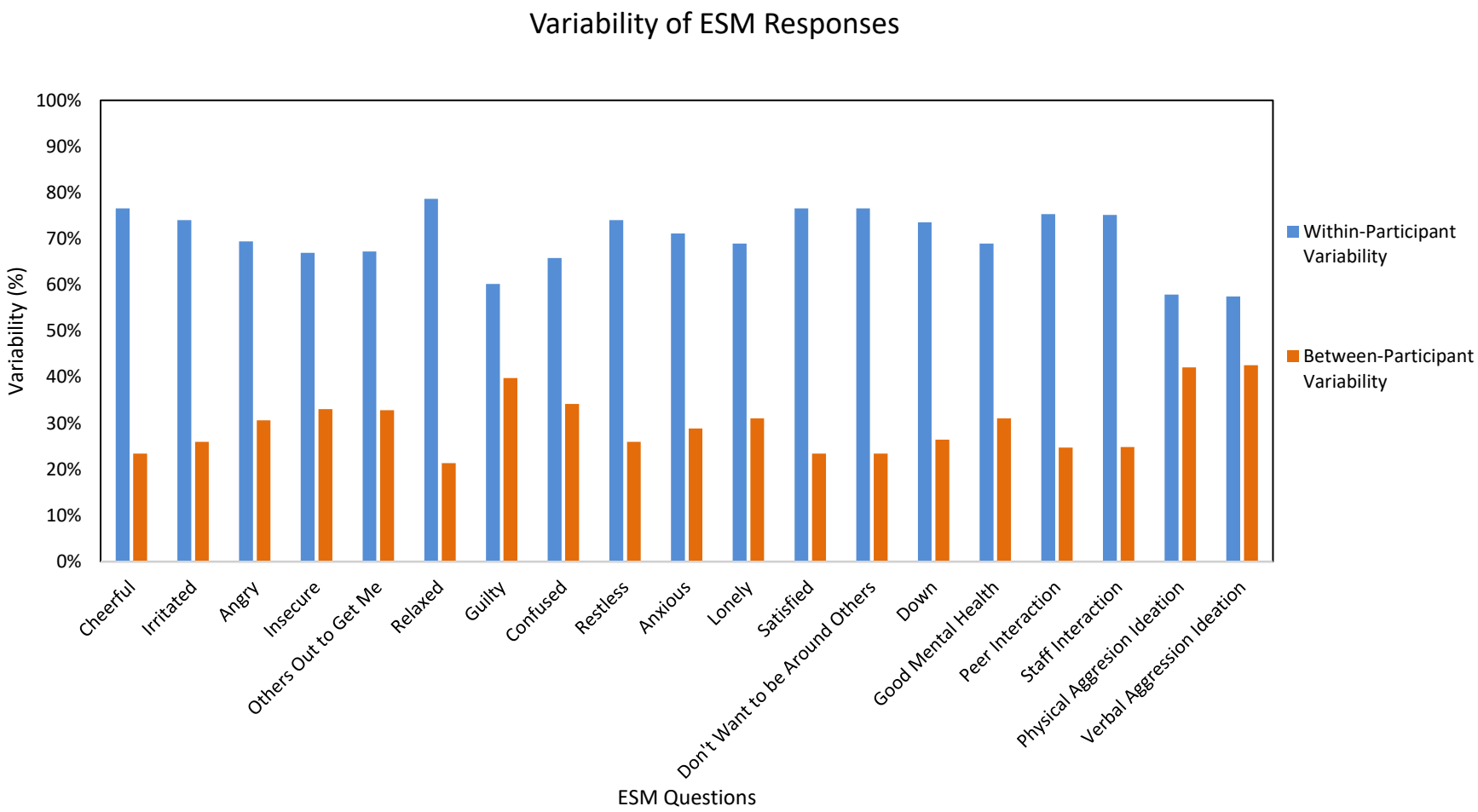

Figure 23 Within- and between-participant variability of ESM questions

6.3.3 Factor Structure and Validity

Table 14 presents the four-factor structure identified through principal components analysis, this accounts for 78% of the variance with good internal consistency for each factor. The pattern matrix and factor rotation matrix are presented in **Table 15** and **Table 16**, respectively. Factors with eigenvalues greater than one were retained, with the four factors group variables relating to Negative Affect (Factor 1), Positive Affect and Social Interaction (Factor 2), Aggressive Ideation (Factor 3), and Isolation (Factor 4). The greatest proportion of variance was explained by Factor 1 (47%), with Factor 4 accounting for the least (6%).

Table 17 presents the multilevel models to assess validity of each factor. The Beta Coefficients indicate the degree of change in the outcome variable when the predictor variable increased by one point. For example, Model 1 shows that when participants' ratings of Positive Affect and Social Interaction increase by one point, their ratings of Negative Affect decreased by 0.3 points. Participants' diagnosis and aggression instances did not have a significant effect in the model.

Table 17 also presents the variance partition coefficients for each factor, which correspond to variability percentages within days (i.e. .26 equals 26% variability). Between-participant variability refers to the percentage of variability in the factor attributed to differences between participants, after accounting for the other three factors. Within-participant variability refers to the percentage of variability in the factor attributed to differences between days or ESM prompts for the same participant, after accounting for the other three factors. Within-participant variability was higher than between-participant variability for each factor, and within-participation variability at the levels of ESM prompts was greater than variability at the level of days for each factor.

Table 14 Principal components analysis (within-participant variability) factor structure (- indicate loadings <.3)

Variable	Factor 1 (Negative Affect)	Factor 2 (Positive Affect and Social Interaction)	Factor 3 (Aggressive Ideation)	Factor 4 (Isolation)
Insecure	.59	-	-	-
Guilty	.55	-	-	-
Confused	.79	-	-	-
Lonely	.61	-	-	-
Don't Want to be Around Others	-	-	-	.84
Cheerful	-	.79	-	-
Relaxed	-	.76	-	-
Satisfied	-	.85	-	-
Good Mental Health	-	.36	-	-
Peer Interaction	-	.83	-	-
Staff Interaction	-	.85	-	-
Irritated	.86	-	-	-
Angry	.78	-	-	-
Others Out to Get Me	.49	-	-	-
Restless	.79	-	-	-
Anxious	.90	-	-	-
Down	.46	-		-
Physical Aggression Ideation	-	-	.89	-
Verbal Aggression Ideation	-	-	.90	-
Eigenvalue	8.99	2.97	1.80	1.06
Variance Explained (%)	47	16	9	6
Cronbach's alpha	.86	.82	.84	-
Mean (SD) (N=41)	1.97 (1.07)	4.69 (1.61)	1.43 (1.03)	2.75 (2.61)

Table 15 Pattern matrix (- indicate loadings <.3)

Variable	Factor1	Factor2	Factor3	Factor4	Uniqueness
Cheerful	-	0.7152	-	-	0.3810
Irritated	-	-	0.7664	-	0.2899
Angry	0.3001	-	0.6944	0.3019	0.3155
Insecure	0.6814	-	0.3084		0.3534
Others Out to Get Me	-	-	0.5306	0.4705	0.4420
Relaxed	-	0.6241	-0.4448	-	0.4092
Guilty	0.7645	-	-	-	0.3347
Confused	0.664	-	0.3696	-	0.3956
Restless	-	-	0.6221	-	0.5360
Anxious	0.3755	-	0.6818	-	0.3560
Lonely	0.7385	-	-	-	0.3754
Satisfied	-	0.7726	-	-	0.3316
Don't Want to be Around Others	0.5991	-	-	-	0.5729
Down	0.3101	-	0.3491	-	0.7060
Good Mental Health	-0.4889	0.3908	-	-0.4268	0.4080
Peer Interaction	-	0.7735	-	-0.3619	0.2561
Staff Interaction	-	0.7747	-	-0.3972	0.2311
Physical Aggression Ideation	-	-	-	0.7958	0.2744
Verbal Aggression Ideation	-	-	-	0.8000	0.2851

Table 16 Factor Rotation Matrix

	Factor1	Factor2	Factor3	Factor4
Factor1	0.5550	-0.4509	0.5781	0.3930
Factor2	0.4259	0.8735	0.1474	0.1840
Factor3	0.4680	-0.0604	0.0991	-0.8761
Factor4	-0.5399	0.1732	0.7964	-0.2103

Table 17 Validity of factors

Model	Outcome	Predictor	Beta Coefficient (SE)	*p*	95% CI Lower	Upper	Variance Partition Coefficients Between-Participant Variability	Within-Participant Variability (Day)	Within-Participant Variability (Prompt)
1	Negative Affect	Diagnosis	.11 (.07)	*p* = .08	-.01	.24			
		Aggression/No Aggression	.18 (.11)	*P* = .10	-.03	.39			
		Positive Affect and Social Interaction	-.30 (.02)	***p* <.001**	-.34	-.27	.26	.21	**.53**
		Aggressive Ideation	.44 (.03)	***p* <.001**	.38	.51			
		Isolation	.24 (.01)	***p* <.001**	.21	.27			
2	Positive Affect and Social Interaction	Diagnosis	-.06 (.14)	*p* = .68	-.32	.21			
		Aggression/No Aggression	.24 (.22)	*P* = .26	-.18	.66			
		Negative Affect	-.69 (.05)	***p* <.001**	-.78	-.60			
		Aggressive Ideation	-.41 (.05)	***p* <.001**	-.51	-.31	.28	.19	**.53**
		Isolation	-.18 (.02)	***p* <.001**	-.22	-.13			
3	Aggressive Ideation	Diagnosis	.04 (.08)	*p* = .62	-.12	.20			
		Aggression/No Aggression	.06 (.13)	*P* = .64	-.19	.31			
		Negative Affect	.44 (.03)	***p* <.001**	.38	.51			
		Positive Affect and Social Interaction	-.18 (.02)	***p* <.001**	-.22	-.14	.27	.17	**.56**
		Isolation	.11 (.01)	***p* <.001**	.08	.14			
4	Isolation	Diagnosis	.03 (.14)	*p* = .84	-.24	.30			
		Aggression/No Aggression	-.25 (.22)	*p* = .26	-.69	.18			
		Negative Affect	1.09 (.07)	***p* <.001**	.97	1.21			
		Positive Affect and Social Interaction	-.35 (.04)	***p* <.001**	-.43	-.26	.22	.21	**.57**
		Aggressive Ideation	.50 (.07)	***p* <.001**	.36	.34			

6.4 Relationship with Aggression

Table 18 presents the results of the multilevel models assessing the relationship between the factors and aggressive behaviour. The 20-minute lagged models reflect whether aggression was significantly predicted by ESM responses recorded within a 20-minute window before the incident. Both physical and verbal aggression were significantly predicted by all factors except Isolation. For both types of aggression Positive Affect and Social Interaction demonstrated a significant inverse relationship and therefore appeared to be protective against the occurrence of aggression. Property aggression was only significantly predicted by Aggressive Ideation. In the 40-minute lagged models, physical aggression was significantly predicted by Positive Affect and Social Interaction, which again demonstrated a significant inverse relationship, and Aggressive Ideation. Verbal aggression was also significantly predicted by Aggressive Ideation, in addition to Negative Affect. Property aggression was not significantly predicted by any factor. No statistically significant findings were identified in the 60-minute lagged models.

After initially modelling the data for all participants this was then disaggregated by diagnostic group (schizophrenia-spectrum condition or dissocial personality disorder) to explore the effect of a schizophrenia-spectrum diagnosis on the relationship between ESM data and aggression (**Table 19**). Similar to **Table 18**, physical and verbal aggression were significantly predicted by increasing Negative Affect and Aggressive Ideation up to 20-minutes before the aggressive outcome occurred. These factors were also significantly predictive in the 40-minute epochs, where reduced Positive Affect and Social Interactions were also found to be significantly predictive. Property aggression was not significantly predicted by any factor across any epoch, and no statistically significant findings were identified across the 60-minute epochs.

Table 18 Relationship between factors and aggressive behaviour

	Outcome Variable (*n incidents)*	Predictor	Beta Coefficient (SE)	*p*	95% CI Lower	Upper
20-Minute Lagged Association	**Physical Aggression**	Negative Affect	.58 (.03)	***p* =.020**	.12	.74
		Positive Affect and Social Interaction	-.56 (.06)	***p* =.002**	.76	-.31
		Aggressive Ideation	.62 (.02)	***p* <.001**	.43	.82
		Isolation	.22 (.01)	*p* =.163	-.09	.53
	Verbal Aggression	Negative Affect	.31 (.05)	***p* =.036**	.02	.60
		Positive Affect and Social Interaction	-.23 (.03)	***p* =.031**	-.44	-.02
		Aggressive Ideation	.54 (.02)	***p* <.001**	.31	.76
		Isolation	.07 (.04)	*p* =.314	-.07	.22
	Property Aggression	Negative Affect	-.14 (.04)	*p* =.741	-.96	.68
		Positive Affect and Social Interaction	.06 (.02)	*p* =.821	-.44	.56
		Aggressive Ideation	.48 (.01)	***p* =.032**	.04	.92
		Isolation	.08 (.01)	p =.637	-.26	.43
40-Minute Lagged Association	**Physical Aggression**	Negative Affect	.26 (.03)	p =.483	-.46	.98
		Positive Affect and Social Interaction	-.55 (.02)	***p* =.041**	-.67	-.02
		Aggressive Ideation	.66 (.03)	***p* =.005**	.20	.79
		Isolation	.15 (.01)	*p* =.389	-.19	.48
	Verbal Aggression	Negative Affect	.38 (.01)	***p* =.029**	.04	.71
		Positive Affect and Social Interaction	-.08 (.02)	*p* =.555	-.34	.18
		Aggressive Ideation	.35 (.03)	***p* =.022**	.05	.66
		Isolation	.05 (.02)	*p* =.602	-.13	.22
	Property Aggression	Negative Affect	-.05 (.03)	*p* =.900	-.91	.80
		Positive Affect and Social Interaction	.40 (.02)	*p* =.209	-.23	.58
		Aggressive Ideation	.28 (.01)	*p* =.341	-.17	.76
		Isolation	.13 (.04)	*p* =.497	-.24	.49
60-Minute Lagged Association	**Physical Aggression**	Negative Affect	.06 (.01)	p =.634	-.26	.28
		Positive Affect and Social Interaction	.15 (.02)	*p* =.635	-.27	.22
		Aggressive Ideation	.09 (.01)	*p* =.551	-.11	.21
		Isolation	.11 (.02)	*p* =.442	-.09	.15

Verbal Aggression	Negative Affect	.18 (.03)	*p* =.618	-.11	.26
	Positive Affect and Social Interaction	.05 (.01)	*p* =.781	-.14	.18
	Aggressive Ideation	.13 (.02)	*p* =.437	-.21	.20
	Isolation	-.10 (.04)	*p* =.689	-.22	.09
Property Aggression	Negative Affect	-.14 (.02)	*p* =.834	-.30	.11
	Positive Affect and Social Interaction	.04 (.01)	*p* =.401	-.19	.13
	Aggressive Ideation	.07 (.02)	*p* =.447	-.16	.15
	Isolation	-.15 (.04)	*p* =.572	-.27	.08

Table 19 Relationship between factors and aggressive behaviour (diagnosis entered into model)

	Outcome Variable (*n incidents)*	Predictor	Beta Coefficient (SE)	*p*	95% CI Lower	Upper
20-Minute Lagged Association	**Physical Aggression**	Negative Affect	.31 (.02)	***p* =.046**	.10	.39
		Positive Affect and Social Interaction	-.21 (.02)	*p* =.072	-.29	.09
		Aggressive Ideation	.16 (.04)	***p* =.038**	-.24	-.05
		Isolation	-.08 (.05)	*p* =.341	-.23	.07
	Verbal Aggression	Negative Affect	.26 (.08)	***p* =.023**	.14	.35
		Positive Affect and Social Interaction	-.18 (.04)	*p* =.084	-.26	.09
		Aggressive Ideation	.08 (.03)	***p* =.039**	-.14	-.04
		Isolation	.08 (.07)	*p* =.069	-.12	.19
	Property Aggression	Negative Affect	-.12 (.04)	*p* =.358	-.24	.17
		Positive Affect and Social Interaction	.04 (.01)	*p* =.242	-.07	.11
		Aggressive Ideation	.18 (.03)	*p* =.466	-.09	.26
		Isolation	.24 (.06)	*p* =.322	-.11	.39
40-Minute Lagged Association	**Physical Aggression**	Negative Affect	.21 (.03)	***p* =.043**	.09	.31
		Positive Affect and Social Interaction	-.22 (.02)	***p* =.037**	-.31	-.06
		Aggressive Ideation	.28 (.04)	***p* =.040**	.07	.36
		Isolation	.11 (.03)	*p* =.343	-.14	.20
	Verbal Aggression	Negative Affect	.19 (.03)	***p* =.041**	.07	.26
		Positive Affect and Social Interaction	-.25 (.04)	***p* =.038**	-.33	-.07
		Aggressive Ideation	.14 (.02)	***p* =.046**	.06	.27
		Isolation	.33 (.06)	*p* =.487	-.11	-.40
	Property Aggression	Negative Affect	-.21 (.04)	*p* =.337	-.28	.08
		Positive Affect and Social Interaction	-.26 (.05)	*p* =.189	-.36	.11
		Aggressive Ideation	.19 (.07)	*p* =.177	-.08	.24
		Isolation	.25 (.06)	*p* =.296	-.09	.34
60-Minute Lagged Association	**Physical Aggression**	Negative Affect	-.07 (.06)	*p* =.425	-.18	.09
		Positive Affect and Social Interaction	-.11 (.04)	*p* =.129	-.25	.04
		Aggressive Ideation	.11 (.04)	*p* =.115	-.10	.19
		Isolation	.09 (.02)	*p* =.236	-.07	.21

Verbal Aggression	Negative Affect	.21 (.03)	*p* =.268	-.03	.28
	Positive Affect and Social Interaction	-.22 (.06)	*p* =.197	-.36	.08
	Aggressive Ideation	.19 (.05)	*p* =.371	-.05	.26
	Isolation	.17 (.06)	*p* =.260	-.07	.24
Property Aggression	Negative Affect	-.12 (.08)	*p* =.189	-.18	.06
	Positive Affect and Social Interaction	.09 (.03)	*p* =.318	-.10	.24
	Aggressive Ideation	.21 (.03)	*p* =.366	-.04	.31
	Isolation	.14 (.06)	*p* =.470	.09	.25

6.5 Discussion

To our knowledge this study is the first to use ESM in an inpatient forensic mental health service to investigate short-term change in dynamic risk factors, and their relationship to aggressive behaviour. As hypothesised, and consistent with the theorised nature of dynamic risk factors in forensic mental health settings (Andrews, 2012; Ward, 2016), participants' responses to each ESM question over the study demonstrated greater within- than between-participant variability. This indicates that participants' responses were not static over time and demonstrated that dynamic factors vary considerably over short time periods (Mastromanno et al., 2018). This supports the suggestion that current assessments of these risk factors may be too infrequent to capture dynamic factor change (Klepfisz et al., 2016), so the ESM approach may afford a more accurate understanding of how these factors change over relatively short time periods.

The proportion of within-participant variation was not consistent for all dynamic risk factors. Aggressive ideation, for example, demonstrated a smaller proportion of within-participant variation relative to between-participant variation than the other risk factors studied. This suggests that rather than considering dynamic and static risk factors as dichotomous as previous research has tended towards, they may be more accurately understood on a continuum of individual variation. This could have implications for treatment efforts (discussed in greater depth later in the thesis), as factors which vary greatly within-individuals may be more amenable to change than those with less individual variation.

By investigating participants' response patterns over multiple timepoints, this study provides evidence of the magnitude of change in these factors. Changes in participants' responses were typically modest, with large variability relatively infrequent (e.g. changing response from 1-7 in the next prompt). Because of this, capturing large shifts in participants ratings of risk factors will be affected by practical implications such as the length of the reporting period and proportion of missing data. These modest changes also illustrate the value of asking service users to rate their own experiences (Duxbury & Whittington, 2005), as small changes may be harder to detect and record through informant-report approaches that are currently used.

Physical and verbal aggression were significantly predicted by changes in aggressive ideation, positive and negative affect up to 40-minutes before the observed aggression. This builds on

previous research suggesting dynamic risk factors may have greater predictive accuracy for imminent than long-term aggression (Ramesh et al., 2018). This has practical implications regarding the support offered to forensic mental health service users, as it suggests a window of opportunity may exist between changes in individuals' risk state and onset of aggression where support could be offered. Together with the earlier evidence provided by this study that these risk factors can change, there may be an opportunity to provide support to reduce the impact of these changes and therefore reduce the risk of aggression occurring. Given the inverse relationship between positive affect and aggression in these models, support could be offered to enhance positive affect, while negative affect and aggressive ideation should be targets of reduction efforts.

6.5.1 Strengths, Limitations and Future Directions

Due to restrictions on digital technology in the recruitment site, pen-and-paper ESM diaries were used. Externally generated timestamps for diary completion could therefore not be generated, meaning strict adherence to the ESM prompts cannot be verified. There is, however, no evidence that participants retrospectively completed the diaries, and previous research conducted in forensic settings has confirmed the viability of the ESM protocol adopted in this study (Humber et al., 2013).

The ESM variables were selected from the systematic review discussed in Chapter 2 and through consultations with service users during the development phase of the study. This ensured that risk factors selected for inclusion were evidence-based and considered relevant by the study population, however, the ESM assessment itself is not an exhaustive list of relevant dynamic risk factors. Future research should ensure that similar assessments can accommodate alternative and/or additional factors whose relevance may change with, for example, setting and population. This study was also conducted in a male medium-security forensic mental health service, therefore future research could examine the relevance of these risk factors in services of higher/lower security, and among women service users.

Good adherence to the ESM protocol was observed, but it is unclear whether this adherence would persist over longer periods and therefore represent a long-term strategy for managing aggression. In addition to investigating long-term adherence, future research could investigate whether adherence and acceptability is affected by the support offered to participants throughout the study in engaging with the monitoring procedure and delivery method for ESM prompts. For example, modern smartphone-facilitated prompts could be considered more practical than paper diaries over longer periods of time but could also pose

challenges for less confident users of technology and represent a security consideration for the forensic mental health setting.

Future research is required to investigate whether ESM recordings of risk are actionable and could provide benefit for service users and staff. For example, it is unclear what level of change in ESM responses staff would consider necessary to act on and whether this threshold would be service user specific. Machine learning approaches could attempt to validate these individual-level thresholds. Future research should also consider exactly what interventions may be triggered by changes in ESM responses and service users' willingness to record information if it risked clinical intervention.

6.6 Chapter Conclusion

This study identified that dynamic risk factors measured using ESM demonstrated a high-degree of within-participant variability. This confirms that these risk factors are capable of change over relatively short periods of time, though these findings also indicated that the magnitude of these changes were often modest. Physical and verbal aggression were predicted by changes in aggressive ideation, negative and positive affect occurring up to 40-minutes before the observed aggressive behaviour. Utilising ESM to monitor changes in these risk factors may therefore provide an earlier indication of heightened aggression risk than possible through existing risk assessment methods. The risk factors investigated in this study are also potentially amenable to intervention, and these findings suggest a window of opportunity may exist between the onset of the risk factor and aggressive outcome in which risk of aggression may be reduced. This represents a potentially valuable area for future research.

Chapter 7 : Real-Time Change in Psychophysiological Risk Factors for Inpatient Aggression

7.1 Introduction

The ESM study in Chapter 6 indicated that dynamic changes in psychological risk factors such as Negative Affect and Aggressive Ideation were significantly predictive of physical and verbal aggressive outcomes up to 40-minutes before the observed act of aggression. These psychological risk factors represent a core component of theoretical models of aggression (Heffernan & Ward, 2017) and also represent key treatment targets (Ward, 2016; Ward & Willis, 2016). In addition to psychological risk factors, neurobiological models developed from laboratory research have emphasised a strong association between aggression and autonomic deregulation (Stahl, 2014), specifically increasing EDA (Armstrong et al., 2019) and reduced HRV (Puhalla et al., 2019), indices of the sympathetic and parasympathetic nervous system, respectively (Boucsein, 1992).

Autonomic abnormalities among individuals diagnosed with schizophrenia-spectrum conditions have been consistently reported. Compared to non-affected individuals, these conditions are associated with significantly reduced vagal tone and HRV (e.g. Cella et al., 2018; Moon et al., 2013) and parasympathetic nervous system activity (Fujibayashi et al., 2009). A systematic review and meta-analysis (Alvares et al., 2016) reported that individuals with schizophrenia-spectrum conditions demonstrated significantly reduced HRV, even after controlling for antipsychotic medication. Similarly, those diagnosed with dissocial personality disorder have consistently reported significant under-arousal in EDA and HRV compared to nonaffected individuals (Raine, 1996; Warburton & Stahl, 2016). While these autonomic abnormalities have been linked to symptoms severity and poorer functional outcomes for service users (Khandoker et al., 2010), there has been relatively little research investigating its relationship with inpatient aggression. Both schizophrenia and dissocial personality disorder diagnoses are prevalent in admissions to forensic services.

Passive remote monitoring technology now enables the collection of psychophysiological data with minimal intrusion into participants' daily activities. Identifying changes in psychophysiological arousal and whether these changes significantly predict future aggression and could support efforts to deescalate potentially aggressive situations by providing an early indication of risk. Tantalisingly, one study (Looff et al., 2019) reported significantly increased EDA and heart rate 30-minutes prior to an aggressive incident suggesting the potential for using this approach.

This study explores the use of a passive remote monitoring device in an inpatient forensic mental health service to achieve two main aims. The first is to investigate the extent to which psychophysiological arousal fluctuates during participants' daily routines. This is an important precondition for individualised prediction models and requires a high-degree of within-participant variability in psychophysiological arousal. The second aim is to investigate whether increasing electrodermal activity and reduced HRV will predict an individual's aggression.

7.2 Method

Ethical approval, participants, contextual clinical and demographic characteristics, aggressive outcome measures and passive remote monitoring technology were previously outlined in Chapter 6.

7.2.1 Procedure

Following informed consent participants were provided with comprehensive instructions for operating the E4. They were asked to wear the device each day during their normal waking hours for seven consecutive days, taking it off only to bathe and sleep and to keep the device charged. Each participant was contacted at least three times over the course of the week to address any questions. This study was conducted and reported following Guidelines for Reporting on Articles on Psychiatry and Heart Rate Variability (Appendix B; Quintana et al., 2016) and reporting guidelines for electrodermal activity measurements (Appendix C; Boucsein et al., 2012).

7.2.1.1 Data Pre-Processing

The first five minutes from each recording file was excluded to allow blood vessels in the wrist time to adapt to compression from the E4's sensors (Taylor et al., 2015). Recordings for each day of participation were segmented into 20- 40- and 60-minute epochs. Raw EDA data were passed through a median filter (window size 44 corresponding to 11 seconds) to remove rapid frequency spikes. Data were then passed through a Butterworth low-pass filter (order = 5; lower cut-off frequency = 0.5) using the MATLAB Ledalab package to remove high frequency noise. Phasic and tonic components of the EDA signal were extracted through continuous decomposition analysis (Benedek & Kaernbach, 2010a, 2010b).

Interbeat intervals were pre-processed in Kubios using its automatic artefact detection algorithm (Lipponen & Tarvainen, 2019). An index of overall movement for each epoch was calculated from the actigraphy sensor by the standard Euclidean metric (Cella et al., 2018). Heart rate variability was calculated based on the mean of interbeat intervals (mean RR),

standard deviation of normal-to-normal interbeat intervals (SDNN), as this measure demonstrates greater accuracy over sampling periods shorter than one hour (Cella et al., 2019), and root mean square of successive differences (RMSSD).

7.2.2 Analysis

STATA 16 was used for all analyses (StataCorp, 2019) and statistical significance was set at $p < .05$. Kolmogorov-Smirnov tests were conducted to explore whether the data were normally distributed, and if not, the data were log-transformed before analysis. Pearson R or Spearman rho correlation coefficients were conducted to assess the relationship between all psychophysiological parameters to assess their validity, and to assess their relationship with physical motion which is known to affect electrodermal activity and HRV are affected by physical motion (Maeda et al., 2011). Analysis was conducted in two stages:

7.2.2.1 Within-Participant Variability

Within- and between-participant variability of the psychophysiological parameters were compared using the XTTABS command. To investigate whether the psychophysiological parameters showed sufficient intraindividual change to be considered a dynamic risk factor we adopted a threshold of 50% within-participant variability. Within-participant variability of 100% would indicate that all variability in psychophysiological arousal was occurring within-participants over time, while 0% variability would indicate that all variability was occurring between-participants and individual participants' psychophysiological arousal was static over time

7.2.2.2 Relationship with Aggression

Multilevel models using the XTMIXED command were conducted to investigate whether changes in EDA and HRV were significantly associated with incidents of aggressive behaviour. There were too few incidents of Autoaggression recorded during the study to construct reliable multilevel models, therefore the analysis was limited to physical, verbal and property aggression. Time-lagged models were conducted using participants' physiological arousal 20, 40 and 60 minutes prior to the recorded aggressive incident, to investigate whether arousal can predict aggression. These time periods were informed by previous research (de Looff et al., 2019) and enabled investigation of whether different window lengths are better suited to capturing change in different parameters. They were also chosen as they could afford a practical window of opportunity in the ward-environment to intervene and de-escalate and aggressive incident. All data were entered into these models to calculate mean psychophysiological arousal for that time window and grouped according to whether i) an

aggressive incident was recorded during this period and if so ii) whether this data point fell within or outside of the time window. Some psychophysiological parameters, such as phasic electrodermal activity, may also be better suited to capturing change in shorter time windows. Diagnosis and symptom severity were entered into the multilevel models separately to investigate their impact on the relationship between psychophysiological parameters and aggression.

7.3 Results

7.3.1 Demographics and Clinical Characteristics

Ninety-seven participants were approached and 41 agreed to participate. Ninety-nine aggressive incidents were reported during the study (Verbal: 75; Physical: 15; Property: 7; Autoaggression: 2). Participants' demographic and clinical characteristics and differences by diagnostic and aggressive groups are presented previously in **Table 11** and **Table 12** in Chapter 6. Intercorrelations among psychophysiological parameters are show in **Table 20**. All parameters, except RMSSD, correlated significantly with each other and physical motion.

Table 20 Correlations between psychophysiological variables

	Phasic	**Tonic**	**RR**	**SDNN**	**RMSSD**	**Motion**
Phasic	-	*r* = .75 *p* <.001	*r* =.69 *p* = .03	*r* = .63 *p* = .01	*r* =.75 *p* = .67	*r* = .56 *p* = .04
Tonic	*r* = .75 *p* <.001	-	*r* = .30 *p* = .04	*r* = .64 *p* = .03	*r* = .54 *p* = .05	*r* = .69 *p* <.001
RR	*r* =.69 *p* = .03	*r* = .30 *p* = .04	-	*r* = .68 *p* <.001	*r* = .78 *p* <.001	*r* = .55 *p* = .04
SDNN	*r* = .63 *p* = .01	*r* = .64 *p* = .03	*r* = .68 *p* <.001	-	*r* = .86 *p* <.001	*r* = .69 *p* < .001
RMSSD	*r* =.75 *p* = .67	*r* = .54 *p* = .05	*r* = .78 *p* <.001	*r* = .86 *p* <.001	-	*r* = .62 *p* = .04
Motion	*r* = .56 *p* = .04	*r* = .69 *p* <.001	*r* = .55 *p* = .04	*r* = .69 *p* < .001	*r* = .62 *p* = .04	-

7.3.2 Within-Participant Variability

The average psychophysiological arousal between diagnostic and aggressive groups are presented in **Figure 24** and **Figure 25**. Participants with a diagnosis of Dissocial Personality

Disorder demonstrated significantly lower SDNN ($F(1,39)=11.41$, $p = .02$) and RR ($F(1,39)=10.97$, $p = .004$) than those with a diagnosis of schizophrenia-spectrum disorder. There were no other statistically significant differences between diagnostic groups. There were no statistically significant differences in psychophysiological arousal between participants who were aggressive during the study versus those who were not.

Figure 26 illustrates the within- and between-participant variability observed for each psychophysiological parameter by diagnostic group. Within-participant variability for all parameters exceeded the 50% threshold to be considered a dynamic risk factor. The average within-participant variability across all parameters was 82.3% (schizophrenia-spectrum condition) and 71.2% (DPD), compared to an 17.7% (schizophrenia-spectrum condition) and 28.8% (DPD) between-participant variability, with Phasic and Tonic activity showing the largest within-participant variability.

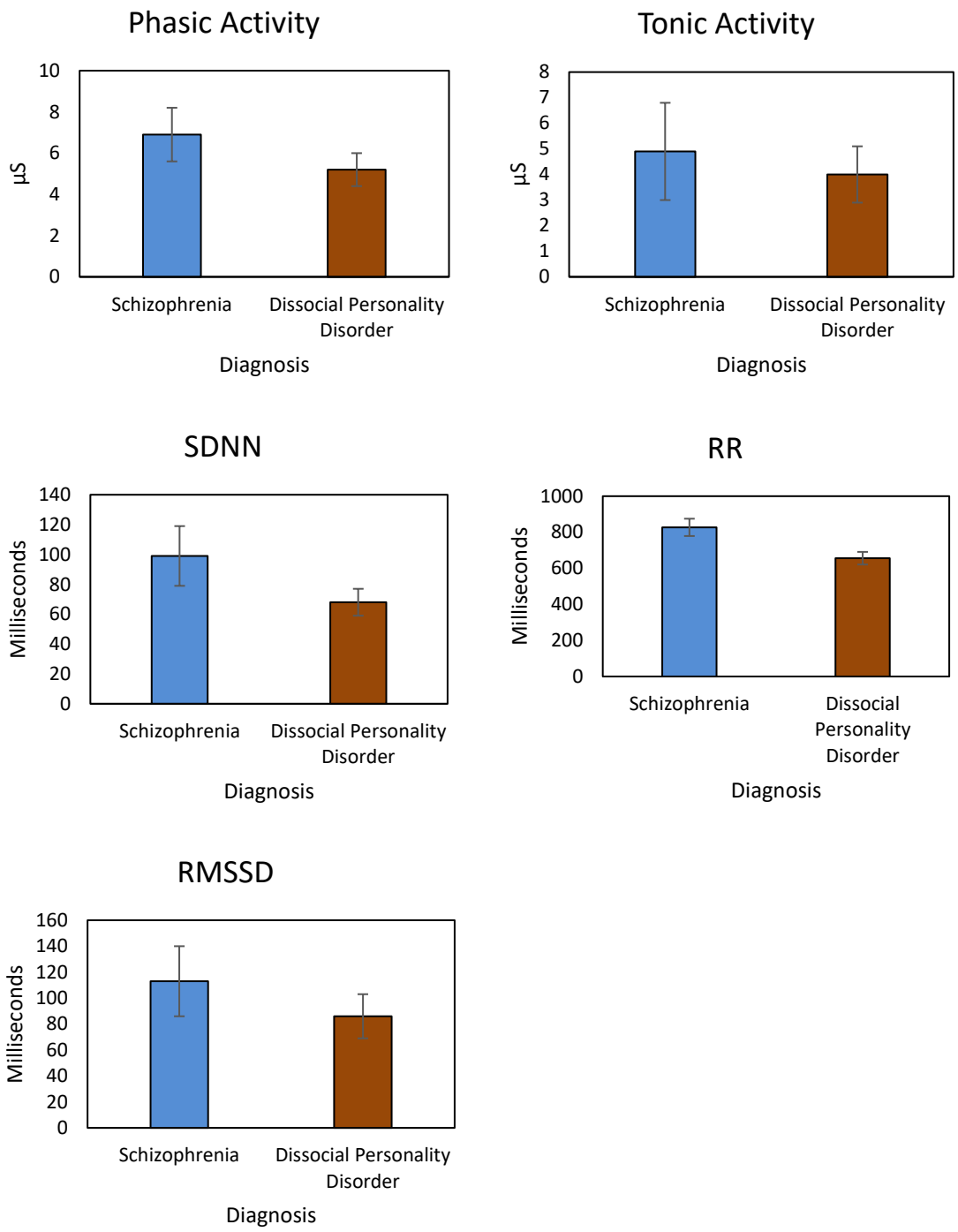

Figure 24 Mean psychophysiological arousal across aggressive groups (error bars=SD)

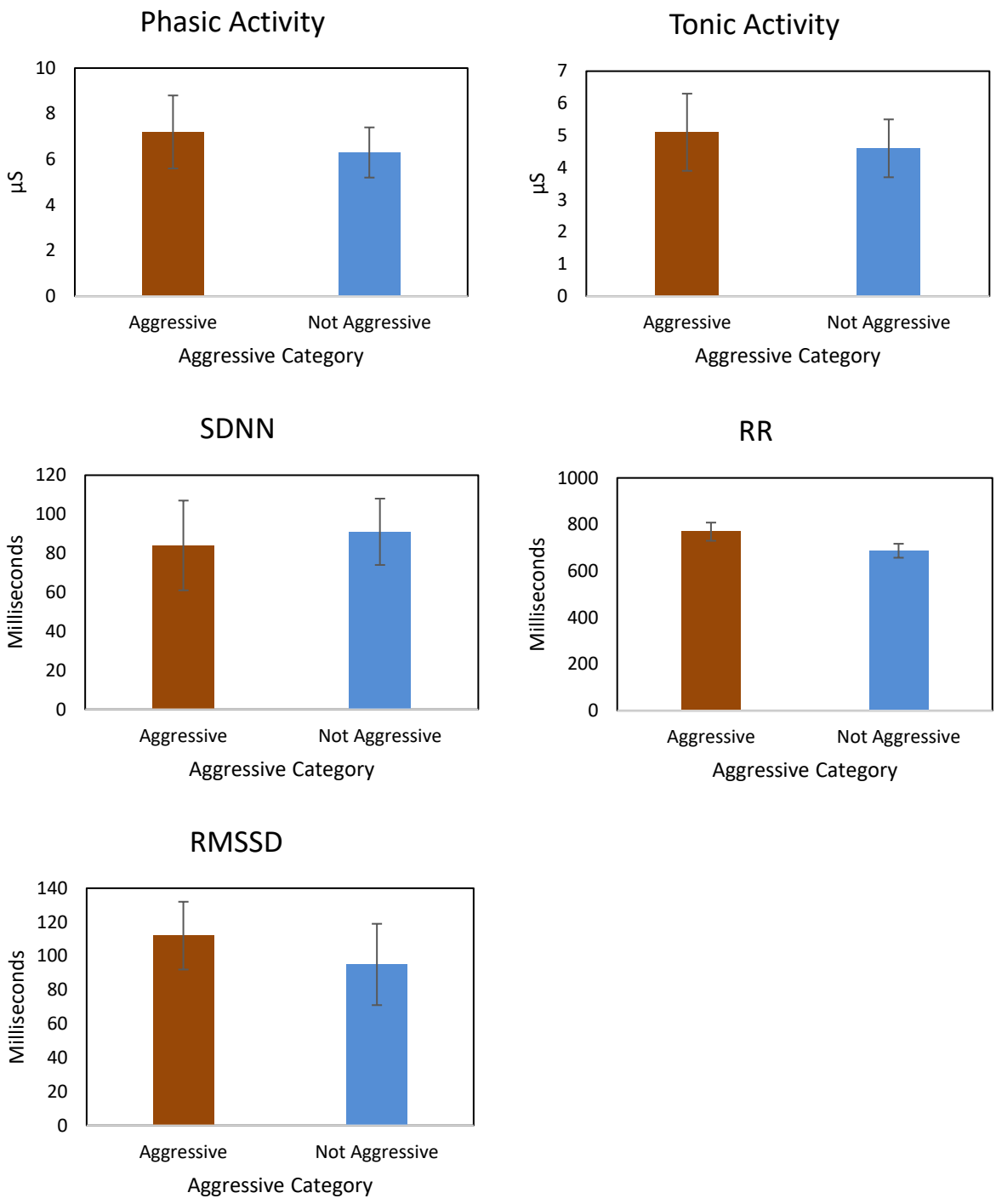

Figure 25 Mean psychophysiological arousal across aggressive groups (error bars=SD)

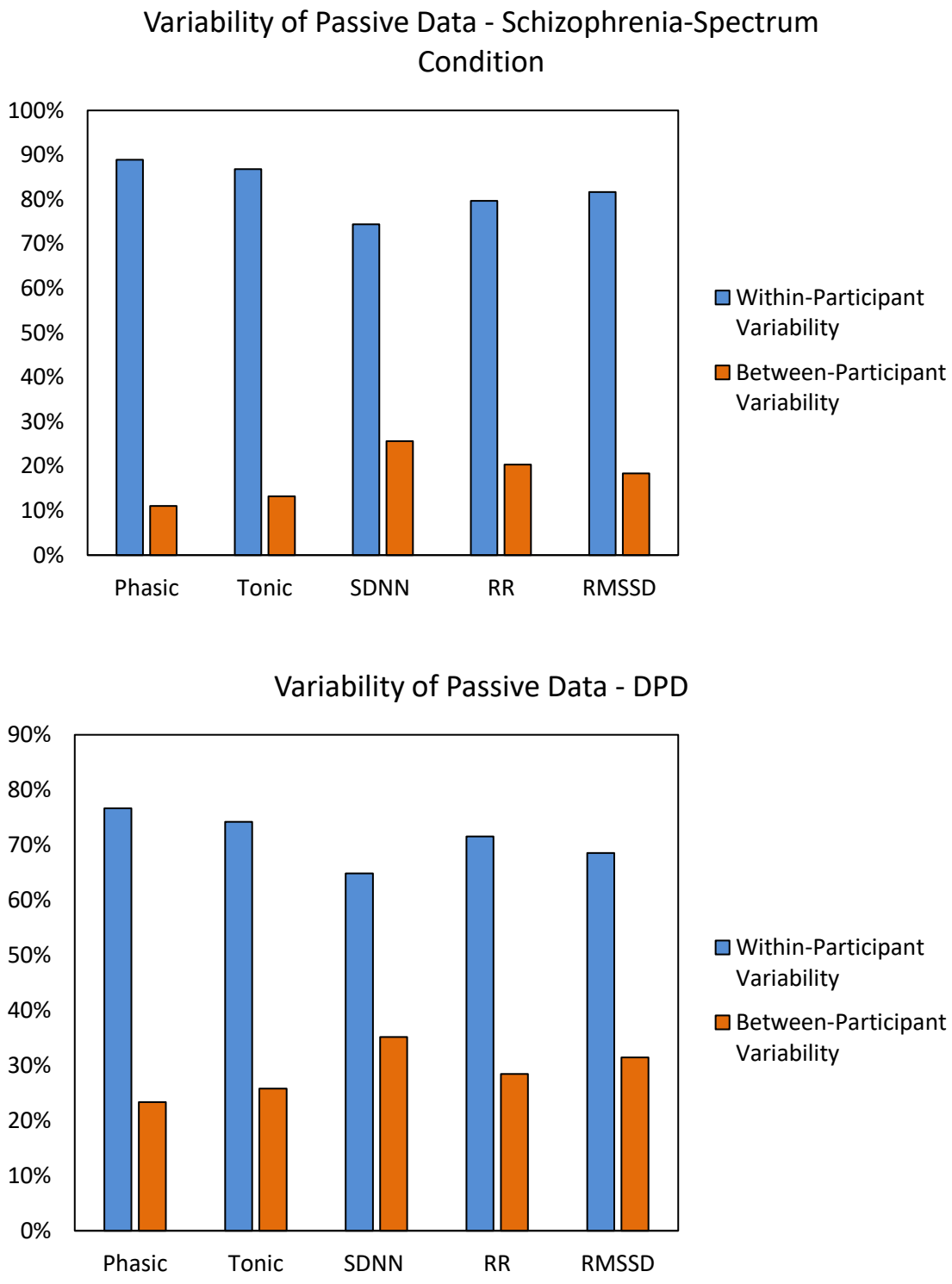

Figure 26 Within- and between-participant variability of psychophysiological parameters by diagnosis

7.3.3 Relationship with Aggression

Table 21 presents the results of the multilevel models assessing the relationship between the factors and aggressive behaviour. Twenty-minutes prior to the aggressive event, physical and verbal aggression were significantly predicted by all psychophysiological parameters except tonic activity. Aggression was predicted by increasing phasic activity and reduced HRV parameters, with these relationships remaining significant after diagnosis and symptom severity were entered into the models. Property Aggression was not significantly predicted by any parameter. Forty-minutes prior to the aggressive event, both physical and verbal aggression were significantly predicted by increased phasic activity and reduced SDNN and RR. Property aggression was not significantly predicted by any parameter across any epoch. There were no statistically significant relationships identified in the 60-minute epochs.

Table 22 presents the results of the multilevel models after disaggregating the passive remote monitoring data by diagnostic group. Similar to the findings reported in **Table 21**, physical and verbal aggression were significantly predicted by increased phasic EDA and decreased HRV 20-minutes before the aggressive outcome occurred. Up to 40-minutes before the aggressive outcome physical and verbal aggression were again significantly predicted by increased phasic EDA and reduced SDNN and RR. Consistent with the data reported in **Table 22**, property aggression was not significantly predicted by any parameter across any epoch, and there were no statistically significant findings reported for any parameter across 60-minute epochs. Differences in mean psychophysiological arousal between epochs in which aggression occurred versus those where no aggression occurred are presented in **Figure 27**.

Table 21 Relationship between factors and aggressive behaviour

	Outcome Variable	Predictor	Beta Coefficient (SE)	*p*	95% CI	
					Lower	Upper
20-Minute Lagged Association	**Physical Aggression**	Phasic Activity	.16 (.01)	***p* =.039**	.09	.25
		Tonic Activity	.23 (.07)	*p* =.131	-35	.43
		SDNN	-.46 (.09)	***p* =.025**	-.86	-.17
		RR	-.21 (.03)	***p* =.029**	-.38	-.12
		RMSSD	-.29 (.08)	***p* =.041**	-.42	-.14
	Verbal Aggression	Phasic Activity	.46 (.02)	***p* =.009**	.16	.81
		Tonic Activity	-.12 (.04)	*p* =.361	-.42	.21
		SDNN	-.15 (.05)	***p* =.018**	-.31	-.06
		RR	-.21 (.17)	***p* =.006**	-.42	-.11
		RMSSD	-.18 (.07)	***p* =.031**	-.30	-.12
	Property Aggression	Phasic Activity	-.15 (.04)	*p* =.817	-.46	.31
		Tonic Activity	.21 (.06)	*p* =.326	-.20	.64
		SDNN	.12 (.06)	*p* =.597	-.15	.35
		RR	.18 (.05)	*p* =.431	-.22	.37
		RMSSD	-.26 (.01)	*p* =.645	-.31	.39
40-Minute Lagged Association	**Physical Aggression**	Phasic Activity	.23 (.05)	***p* =.014**	.11	.38
		Tonic Activity	-.06 (.02)	*p* =.418	-.21	.16
		SDNN	-.18 (.02)	***p* =.031**	-.34	-.09
		RR	-23 (.04)	***p* =.040**	-.41	-.18
		RMSSD	-.12 (.08)	*p* =.187	-.19	.14
	Verbal Aggression	Phasic Activity	.29 (.03)	***p* =.021**	.17	.36
		Tonic Activity	.18 (.07)	*p* =.297	-.12	.26
		SDNN	-.21 (.06)	***p* =.026**	-.32	-.15
		RR	-.23 (.09)	***p* =.031**	-.35	-.19
		RMSSD	.11 (.06)	*p* =.287	-.18	26
	Property Aggression	Phasic Activity	-.08 (.05)	*p* =.598	-.16	.28
		Tonic Activity	-.12 (.07)	*p* =.169	-.28	.45
		SDNN	.16 (.01)	*p* =.098	-.11	.26
		RR	.20 (.05)	*p* =.381	-.19	.32
		RMSSD	.18 (.02)	*p* =.242	-.36	.25
60-Minute Lagged Association	**Physical Aggression**	Phasic Activity	-.28 (.07)	*p* =.494	-.35	.42
		Tonic Activity	.20 (.01)	*p* =.261	-.11	.32
		SDNN	.09 (.02)	*p* =.115	-.06	.21
		RR	.11 (.05)	*p* =.164	-.20	.19
		RMSSD	.18 (.02)	*p* =.264	-.11	.45
	Verbal Aggression	Phasic Activity	.09 (.05)	*p* =.231	-.08	.33
		Tonic Activity	-.11 (.06)	*p* =.087	-.19	.22
		SDNN	.16 (.04)	*p* =.431	-.09	.32
		RR	-.14 (.01)	*p* =.064	-.19	.28
		RMSSD	.19 (.02)	*p* =.424	-.11	.31
	Property Aggression	Phasic Activity	-.18 (.03)	*p* =.231	-.22	.24
		Tonic Activity	.16 (.09)	*p* =.537	-.11	.31
		SDNN	.17 (.03)	*p* =.320	-.22	.35
		RR	.09 (.02)	*p* =.413	-.12	.20
		RMSSD	.16 (.04)	*p* =.073	-.06	.22

Table 22 Relationship between factors and aggressive behaviour (diagnosis entered into model)

	Outcome Variable	Predictor	Beta Coefficient (SE)		95% CI	
				p	Lower	Upper
20-Minute Lagged Association	**Physical Aggression**	Phasic Activity	.27 (.03)	***p* =.033**	.11	.36
		Tonic Activity	.31 (.05)	*p* =.057	-04	.39
		SDNN	-.39 (.07)	***p* =.036**	-.75	-.24
		RR	-.25 (.08)	***p* =.024**	-.36	-.15
		RMSSD	-.17 (.04)	***p* =.046**	-.29	-.05
	Verbal Aggression	Phasic Activity	.44 (.03)	***p* =.013**	.26	.57
		Tonic Activity	.09 (.01)	*p* =.077	-.12	.20
		SDNN	-.24 (.02)	***p* =.027**	-.39	-.09
		RR	-.33 (.06)	***p* =.016**	-.49	-.14
		RMSSD	-.27 (.05)	***p* =.039**	-.36	-.18
	Property Aggression	Phasic Activity	-.08 (.01)	*p* =.225	-.22	.15
		Tonic Activity	.11 (.02)	*p* =.179	-.06	.24
		SDNN	.09 (.03)	*p* =.251	-.18	.26
		RR	.17 (.05)	*p* =.347	-.11	.32
		RMSSD	.22 (.02)	*p* =.327	-.18	.34
40-Minute Lagged Association	**Physical Aggression**	Phasic Activity	.18 (.06)	***p* =.027**	.08	.29
		Tonic Activity	.09 (.03)	*p* =.062	-.11	.21
		SDNN	-.15 (.04)	***p* =.039**	-.27	-.04
		RR	-31 (.06)	***p* =.046**	-.47	-.12
		RMSSD	.08 (.02)	*p* =.072	-.10	.21
	Verbal Aggression	Phasic Activity	.24 (.06)	***p* =.036**	.09	.32
		Tonic Activity	.05 (.01)	*p* =.163	-.08	.14
		SDNN	-.14 (.03)	***p* =.029**	-.27	-.07
		RR	-.18 (.06)	***p* =.035**	-.29	-.11
		RMSSD	.24 (.04)	*p* =.097	-.06	.31
	Property Aggression	Phasic Activity	-.12 (.02)	*p* =.472	-.25	.03
		Tonic Activity	-.33 (.04)	*p* =.291	-.39	.11
		SDNN	.09 (.02)	*p* =.127	-.08	.15
		RR	.11 (.05)	*p* =277	-.16	.21
		RMSSD	.23 (.10)	*p* =.351	-.07	.34
60-Minute Lagged Association	**Physical Aggression**	Phasic Activity	-.11 (.07)	*p* =.326	-.21	.15
		Tonic Activity	.04 (.02)	*p* =.185	-.17	.11
		SDNN	.16 (.03)	*p* =.232	-.09	.25
		RR	.28 (.03)	*p* =.291	-.06	.33
		RMSSD	.24 (.07)	*p* =.306	-.06	.31
	Verbal Aggression	Phasic Activity	.17 (.03)	*p* =.281	-.12	.25
		Tonic Activity	.10 (.04)	*p* =.149	-.05	.19
		SDNN	.07 (.05)	*p* =.317	-.13	.18
		RR	.20 (.07)	*p* =.091	.04	.36
		RMSSD	.08 (.01)	*p* =.308	-.06	.16
	Property Aggression	Phasic Activity	-.09 (.05)	*p* =.362	-.17	.11
		Tonic Activity	.06 (.02)	*p* =.408	-.10	.16
		SDNN	.11 (.03)	*p* =.272	-.05	.28
		RR	.04 (.02)	*p* =.381	-.20	.13
		RMSSD	.26 (.03)	*p* =.151	-.03	.35

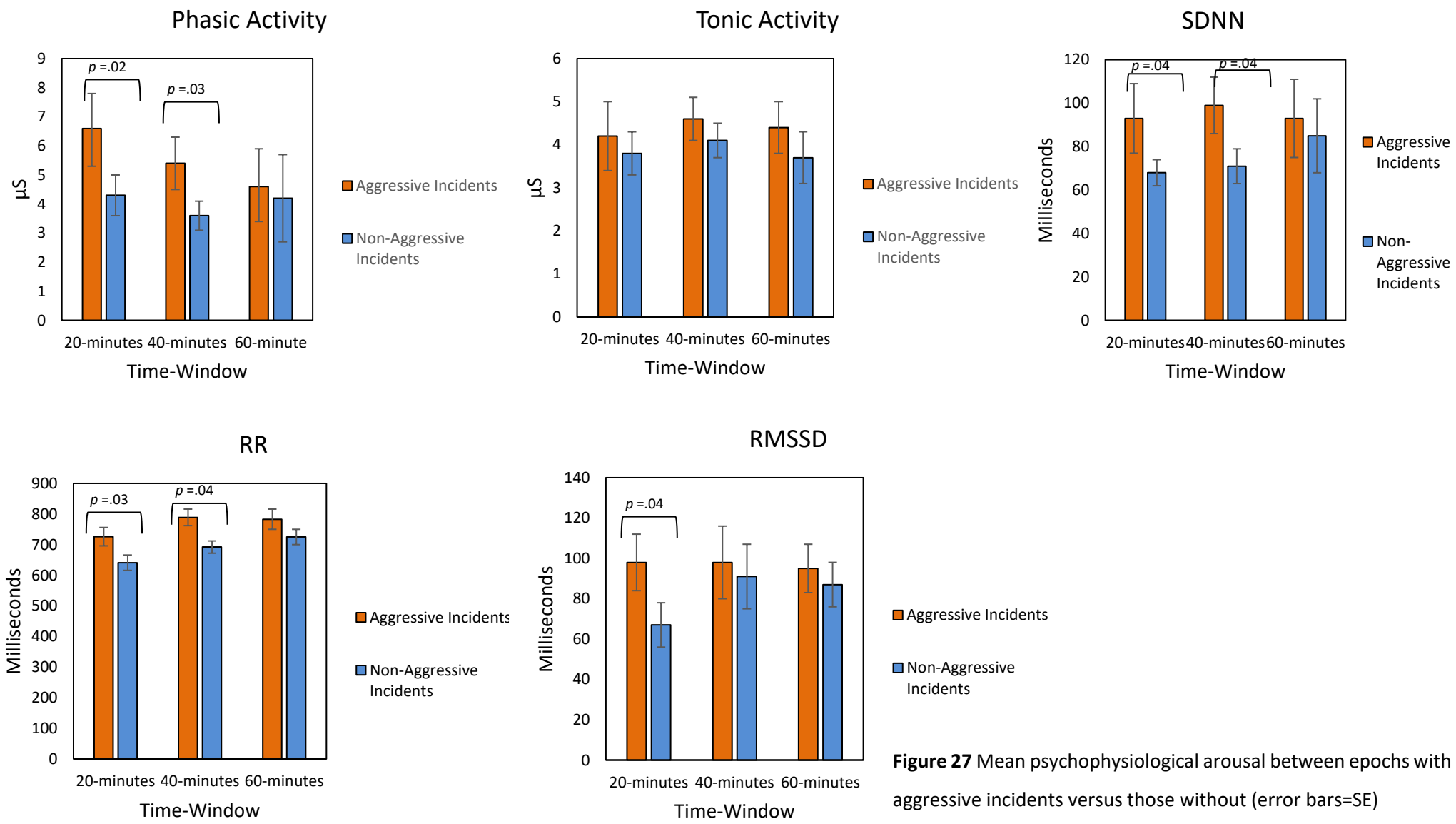

Figure 27 Mean psychophysiological arousal between epochs with aggressive incidents versus those without (error bars=SE)

7.4 Discussion

To our knowledge this is the first study to continuously monitor psychophysiological parameters in an inpatient forensic mental health service using a passive remote monitoring device. As hypothesised, all psychophysiological parameters demonstrated a high degree of within-participant variability (i.e. do not remain static over time). The data supports the hypotheses of links between autonomic deregulation and aggression although this depends on the time window of the measurement. Significantly increased EDA and reduced HRV were reported 20- and 40-minutes before incidents of physical and verbal aggression, but this relationship was not observed at 60-minute intervals or for property aggression.

These findings are consistent with neurobiological models of aggression in mental health which suggest autonomic deregulation contributes to aggression among forensic mental health service users (Scarpa et al., 2010; Weiss, 2012). Indices of psychophysiological activity have not been a feature of historical or contemporary risk assessments (Andrews, 2012), in part due to previous limits of technology. Novel technologies are increasingly being implemented in mental health services (Tully et al., 2015; Tully et al., 2014), with recommendations that these technologies be used to enhance current risk management practices (Ramesh et al., 2018). These findings suggest that psychophysiological arousal. in conjunction with psychological and behavioural risk factors, could support efforts to identify and manage risk of inpatient aggression.

This study builds on the earlier findings of de Looff et al. (2019) by further clarifying the temporal relationship between psychophysiological arousal and inpatient aggression. Significantly increased EDA and reduced HRV were reported 20-minutes prior to physical and verbal aggression being observed and were still obvious 40-minutes prior to the aggressive behaviour. This suggests that a window of opportunity exists between the initial changes in psychophysiological arousal and eventual aggressive outcome to intervene and prevent the aggressive outcome occurring.

The lack of statistically significant relationship in the 60-minute models suggests that psychophysiological arousal and aggression may be characterised by short-term peaks in arousal. This is consistent with the predictive accuracy of contemporary risk assessments, which demonstrate poorer predictive accuracy for longer term aggression (Fazel et al., 2012). Other explanations which may account for these non-statistically significant findings include higher noise-to-signal ratio and artefacts, arising from sources such as physical motion, which may be detected over longer recording (Shaffer & Ginsberg, 2017), 60-minute epochs

providing sufficient time for psychophysiological recovery and reduced reliability of some psychophysiological parameters, particularly HRV parameters, over longer recording periods.

7.4.1 Strengths and Limitations

Similar to the staff and service user pilot study discussed in Chapter 4, participants demonstrated good levels of adherence to the passive remote monitoring procedure, but it is unclear whether adherence would be sustained over longer periods as they were contacted at least three times during the week. This has implications for the viability of passive remote monitoring in a clinical context.

While the number of aggressive incidents was comparable to previous research, the relatively short timeframe limited the opportunity to investigate less common forms of aggression. For example, reliable models could not be conducted for autoaggression due to the low number of incidents recorded. Sample sizes between diagnostic groups were also unequal which may have contributed to unequal variance and subsequently affected statistical power (Rusticus & Lovato, 2014)

7.4.2 Future Directions

The qualitative study with staff discussed in Chapter 3 indicated that while passive remote monitoring technology should not replace existing face-to-face care, it could support staff decisions and prompt earlier support. Investigations of whether continuous passive remote monitoring can provide actionable information for staff members and how this support may be triggered would now be valuable. For example, participants in the earlier qualitative study drew parallels with existing ward-based alarm systems which are automatically triggered. Further developments to build automatic pipelines for data analysis and presentation to staff members are also essential so passive remote monitoring data can be acted on in a timely manner.

Passive remote monitoring could be integrated into existing therapeutic frameworks to support service users' understanding of, for example, the link between cognition, emotional experiences and behaviour in the case of cognitive behaviour therapy. Presenting the data collected by these devices to users may offer a more 'objective' illustration of how their emotional experiences manifest in terms of their psychophysiological arousal and the impact this has for their interactions with others. Passive remote monitoring could also support novel biofeedback interventions for service users and this possibility is discussed in greater detail in the Discussion chapter. Providing service users with objective evidence of their own

increasing levels of arousal could help them to self-regulate their arousal without the need for staff intervention. For example, significant reductions in anxiety have followed HRV biofeedback interventions (Beckham et al., 2013; Schoenberg & David, 2014).

7.5 Chapter Conclusion

This study reported a similar pattern of findings to those identified in the ESM study in Chapter 6. All psychophysiological risk factors demonstrated a high degree of within-participant variability, indicating that psychophysiological arousal was not static within participants. Physical and verbal aggression were significantly predicted by increasing EDA and reduced HRV occurring up to 20- and 40-minutes before the observed aggressive behaviour. These statistically significant relationships were not identified for the 60-minute epochs, potentially indicating psychophysiological recover occurring during this period. Overall, these findings suggest that dynamic changes in psychophysiological arousal may provide a window of opportunity in which appropriate intervention and support might reduce the risk of the aggressive event occurring. This may represent an avenue of future research to investigate whether achieving reductions in psychophysiological arousal can have a concordant reduction in the likelihood of aggression occurring. These findings, together with those reported in the ESM study in Chapter 6, also provide a basis for investigating the combined predictive relationship of ESM and psychophysiological data on inpatient aggression, reported in the following chapter.

Chapter 8 : Predicting Inpatient Aggression with Blended Active and Passive Remote Monitoring

8.1 Introduction

The ESM and passive remote monitoring studies reported in Chapters 6 and 7 indicate that dynamic changes in psychological and psychophysiological risk factors are significantly predictive of inpatient aggression up to 40-minutes before the observed act of aggression. While previous research implementing ESM or passive remote monitoring in forensic mental health settings is limited, these methods have been used independently in a variety of clinical populations and settings and were shown to be feasible and acceptable (Cella et al., 2018; Edwards et al., 2016; Oorschot et al., 2013). Blended approaches which combine both monitoring methods have also been increasingly used, for example, to investigate fluctuations in symptoms of psychosis (Cella et al., 2019) and relapse in major depressive disorder (Matcham et al., 2019). There is limited research implementing passive remote monitoring and ESM in forensic settings (de Looff et al., 2019; Humber et al., 2013) and to our knowledge no previous research investigating a blended approach.

A blended approach also allows us to include additional factors that are known to be affected among forensic mental health service users. Previous research reported significant difficulties in areas such as memory, IQ and executive function (Sedgwick et al., 2017), facial emotion recognition (Bulgari et al., 2020) and theory of mind (Engelstad et al., 2019) in forensic mental health service users. These difficulties may increase the risk of aggression by contributing to difficulties with social interactions, reducing problem-solving abilities and engagement with psychological therapies (Sedgwick et al., 2017), but they have also been associated with autonomic deregulation among individuals with schizophrenia-spectrum conditions (Jáuregui et al., 2011; Okruszek et al., 2017). A blended remote monitoring approach offers an opportunity to assess how these processes relate to passive remote monitoring and ESM parameters during a participant's normal daily routines as opposed to an artificial laboratory setup.

It is currently unclear how short-term fluctuations in both psychological and psychophysiological parameters affect risk of inpatient aggression. It is also unclear whether neuropsychological and social cognitive functioning relate to ESM and passive remote monitoring parameters and influence the relationship between these parameters and aggression. This study combines passive remote monitoring using a wearable wristband and

ESM in an inpatient forensic mental health service to investigate if momentary fluctuations in psychological and psychophysiological risk factors predict inpatient aggression. Based on previous research in community settings and cross-sectional laboratory studies, it is expected that elevations in negative affect, aggressive ideation and electrodermal activity, and reductions in positive affect and HRV, will predict inpatient aggression. Based on previous research linking neuropsychological and social cognitive difficulties with psychophysiological deregulation in clinical populations, it is expected that these difficulties will also be associated with elevated EDA and reduced HRV, respectively.

8.2 Method

Ethical approval, participants, ESM and passive remote monitoring measures and aggressive outcome measures were previously outlined in Chapter 6.

8.2.1 Measures

8.2.1.1 Contextual Clinical and Demographic Characteristics

Demographics (age and ethnicity), current diagnosis (ICD-10), length of treatment within the service and current antipsychotic medications (converted to chlorpromazine equivalents; Woods, 2003) were extracted from participants' electronic hospital records. In addition, the following clinical characterisation measures were used:

Psychopathy: Psychopathy Checklist-Revised; PCL-R (Hare, 1991) is a 20-item scale of psychopathy, a trait with significant associations with aggression and antisocial behaviour (Leistico et al., 2008), completed by trained clinical staff members within the service.

Symptom Severity: Brief Psychiatric Rating Scale; BPRS (Overall & Gorham, 1962) is a 24-item scale based on participant self-report and observed behaviour and speech, with ratings based on the previous two weeks.

Behavioural Inhibition/Activation: Behavioural Inhibition System/Behavioural Activation System; BIS/BAS (Carver & White, 1994) is a 24-item self-assessment of behavioural avoidance and impulsivity. Scores relate to four domains: Impulsivity, Drive, Fun Seeking and Reward Responsiveness.

8.2.1.2 Social Cognitive Markers of Psychophysiological Deregulation

Facial Emotion Recognition: Penn Emotion Recognition Test; ER-40 (Carter et al., 2009) required participants to correctly identify emotions (happy, sad, angry, fearful, neutral) from 40 colour photographs. Performance was assessed based on the total number of correct answers, and proportion of correct answers for each emotion category.

Hostile Attribution Bias: Ambiguous Intention and Hostility Questionnaire; AIHQ (Combs, Penn, Wicher, & Waldheter, 2007) required participants to read five vignettes of an ambiguous situation and rate why the situation occurred, whether it occurred on purpose and what action they would take, providing an overall hostile attribution bias score.

Theory of Mind: Hinting Task (Corcoran et al., 1995) required participants to read 10 stories involving two characters in a conversation and decide on the underlying meaning behind their conversation, with answers scored based on whether they were verbatim or reflected an understanding of the underlying meaning.

Emotional Intelligence: Trait Emotional Intelligence Questionnaire – Short Form; TEIS (Petrides, 2009) is a 30-item assessment providing a global emotional intelligence score.

8.2.1.3 Neuropsychological Markers of Psychophysiological Deregulation

Estimated Full Scale IQ (FSIQ): Wechsler Test of Adult Reading; WTAR (The Psychological Corporation, 2001) estimated premorbid intelligence and required participants to correctly pronounce 50 irregularly spelled words with unusual grapheme-to-phoneme translations.

Processing Speed and Mental Flexibility: Trail Making Task; TMT (Reitan & Wolfson, 1985) required participants to draw a line connecting 25 numbers sequentially (Part A) and 12 numbers and letters in ascending numerical and alphabetical order (Part B). The time taken to complete both tasks was recorded and a mental flexibility score calculated by subtracting the completion time for Part A from B.

Working Memory: Digit Span (Woods et al., 2011) required participants to repeat a sequence of numbers in the same (forward recall condition) or reverse (backward recall condition) order that they are presented, up to a maximum of 14 trials. Sequences began at three digits (two digits for the backward recall condition) and increased by one with every correct trial. The number of digits correctly recalled before two consecutive wrong answers was recorded (2E Max).

8.2.2 Procedure

The ESM and passive remote monitoring procedure were previously outlined in Chapters 6 and 7, respectively.

8.2.2.1 Data Pre-Processing

a) Passive Remote Monitoring

The first five minutes from each recording file was excluded to allow blood vessels in the wrist time to adapt to compression from the E4's sensors (Taylor et al., 2015). Recordings for each day of participation were segmented into 20- 40- and 60-minute epochs. Raw EDA data were passed through a median filter (window size 44) to remove rapid frequency spikes. Data were then passed through a Butterworth low-pass filter (order = 5; lower cut-off frequency = 0.5) using the MATLAB Ledalab package to remove high frequency noise. Phasic and tonic components of the EDA signal were extracted through continuous decomposition analysis (Benedek & Kaernbach, 2010a, 2010b).

Interbeat intervals were pre-processed in Kubios using its automatic artefact detection algorithm (Lipponen & Tarvainen, 2019). An index of overall movement for each epoch was calculated from the actigraphy sensor by the standard Euclidean metric (Cella et al., 2018). Heart rate variability was calculated based on the mean of interbeat intervals (mean RR), standard deviation of normal-to-normal interbeat intervals (SDNN), as this measure demonstrates greater accuracy over sampling periods shorter than one hour (Sollers et al., 2007), and root mean square of successive differences (RMSSD).

b) Experience Sampling Methodology

Responses which were not recorded within 20-minutes of the ESM prompt were labelled as missing, with multiple imputation used to handle missing responses. Participants who had responded to less than 20% of prompts were excluded from the analyses (Oorschot et al., 2013). ESM prompts were then matched to the passive remote monitoring data using a purposefully developed Python code due to the differing temporal resolutions between these data sources. This corresponded to 10,800 EDA and 172,800 HRV data points for every 45-minute ESM prompt window.

8.2.2.2 Analysis

STATA 16 was used for all analyses (StataCorp, 2019) and statistical significance was set at $p < .05$. Previous research has reported differences in clinical characteristics between service users with schizophrenia-spectrum conditions and dissocial personality disorder (Sedgwick et al., 2017, 2018), therefore chi-square tests and independent *t*-tests were used to explore whether demographic and cognition characteristics differed significantly according to diagnosis and between participants who had exhibited aggression during the study versus those who had not.

Time-lagged multilevel models were conducted based on participants' ESM responses and physiological arousal 20-, 40- and 60-minutes prior to the recorded aggression to investigate whether these variables predicted aggression within these time periods. These time periods were chosen based on previous research (Looff et al., 2019) and because they could afford a practical window of opportunity in the ward-environment to intervene and de-escalate and aggressive incident.

All datapoints were entered into these models and grouped according to whether i) an aggressive incident was recorded during this period and if so ii) whether this data point fell within or outside of the time window. The clinical characteristics, neuropsychological and social cognition measures used in this study do not possess the multilevel structure of the ESM and passive data and cannot be entered into the multilevel models without violating the assumption that they are repeated measures. Partial correlations controlling for the effect of diagnosis were initially performed with the mean value of each ESM and passive remote monitoring variable across the seven-day period. This data was then median split and entered into the multilevel models to investigate their influence on psychophysiological deregulation and relationship with aggression.

Diagnosis was also controlled as previous research reported a significant relationship between psychophysiological deregulation, neuropsychological and social cognitive functioning and diagnosis, particularly schizophrenia-spectrum conditions. This analysis will indicate the contribution of clinical characteristics, neuropsychological and social cognitive difficulties to psychological and psychophysiological deregulation and aggression, over and above the influence of diagnosis reported by previous research. These findings will provide a novel understanding of the interactions between these clinical characteristics, psychological processes and psychophysiological deregulation in participants typical daily environment, which may reflect a potential mechanism through which this deregulation influences the likelihood of aggression.

To control for the multiple correlational analyses conducted when analysing the neuropsychological and social cognitive difficulties, which would increase the risk of a type one error, the Benjamini and Hochberg false discovery rate was used (Benjamini & Hochberg, 1995). This method calculates a critical value, based on the number of tests conducted, against which the original p value is compared and a significance threshold of $p < .05$ is retained. This method also maximises the statistical power of the findings compared to alternative multiple comparison correction methods (Noble, 2009). By accounting for the

nested structure of the data, multilevel modelling is robust against multiple comparisons compared to approaches which fail to account for data clustering and inflate the type one error rate (Aarts et al., 2015). Multiple comparison corrections were therefore not applied to the multilevel models.

8.3 Results

8.3.1 Demographics and Clinical Characteristics

Ninety-seven participants were approached and 41 agreed to participate (78% schizophrenia-spectrum condition). Ninety-nine aggressive incidents were reported during the study (Verbal: 75; Physical: 15; Property: 7; Autoaggression: 2). Too few incidents of Autoaggression were recorded during the study meaning reliable multilevel models could not be constructed for this outcome. analysis was limited to physical, verbal and property aggression. Participants' demographic and clinical characteristics and differences by diagnostic group are presented in **Table 23**. Participants with a sole diagnosis of dissocial personality disorder were significantly older, had a higher level of psychopathy, had received treatment within the service for a significantly longer period and were prescribed a significantly lower dose of antipsychotic medication, but did not differ significantly in symptom severity, than participants with a schizophrenia-spectrum diagnosis. Participants with a schizophrenia-spectrum diagnosis were significantly more likely to come from a Black, Asian and Minority Ethnic background.

Table 24 illustrates the differences in demographic and clinical characteristics according to whether participants exhibited aggression during the study. Participants who were aggressive scored significantly higher on the BPRS and demonstrated a significantly greater hostile attribution bias than those who were not aggressive. No other statistically significant differences were observed.

Table 23 Participant clinical and demographic characteristics

Measure	Total Sample (*N* = 41)	Schizophrenia-Spectrum Condition (*N* = 32)	Dissocial Personality Disorder (*N* = 9)	Group Differences	Direction of Effect
Demographics					
Age; Mean (SD)	39.78 (10.96)	37.16 (10.20)	49.11 (8.46)	$t(39)=-3.21$, $p=.003$	DPD>SCZ
Ethnicity (*N*)					
Black British	16	16	0		
White British	15	6	9		
Black Caribbean	5	5	0	$\chi^2(4)=19.99$, $p=.001$	
Black African	3	3	0		
Asian	2	2	0		
Clinical Characteristics					
Treatment Length (Years); Mean (SD)	2.76 (1.74)	2.24 (1.47)	4.58 (1.40)	$t(39)=-4.26$, $p<.001$	DPD>SCZ
Chlorpromazine Equivalent Dosage; Mean (SD)	373.17 (178.92)	434.38 (134.07)	155.56 (148.84)	$t(39)=5.39$, $p<.001$	SCZ>DPD
PCL-R; Mean (SD)	19.05 (7.32)	17.06 (6.68)	26.11 (4.81)	$t(39)=-3.78$, $p=.001$	DPD>SCZ
BPRS; Mean (SD)	51.83 (12.83)	52.81 (13.24)	48.33 (11.05)	$t(39)=.93$, $p=.360$	-
BIS/BAS; Mean (SD)					
Impulsivity	18.37 (4.19)	18.07 (4.09)	19.50 (4.66)	$t(39)=-.86$, $p=.398$	-
Drive	11.71 (7.89)	12.10 (2.60)	10.25 (3.62)	$t(39)=1.64$, $p=.109$	-
Fun Seeking	10.92 (3.23)	10.97 (3.65)	10.75 (1.75)	$t(39)=.16$, $p=.872$	-
Reward Responsiveness	15.95 (3.30)	15.90 (3.55)	16.13 (2.30)	$t(39)=-.17$, $p=.867$	-
Social Cognition					
ER-40					
Total Correct; Mean(SD)	27.03 (6.05)	26.50 (6.52)	28.88 (3.80)	$t(39)=-.98$, $p=.335$	-
Proportion Correct (%)					
Happy	85.42 (19.71)	82.59 (21.34)	95.31 (6.47)	$t(39)=-1.65$, $p=.108$	-
Sad	71.88 (21.00)	69.20 (21.38)	81.25 (17.68)	$t(39)=-1.46$, $p=.155$	-
Anger	52.78 (22.18)	57.14 (22.16)	37.50 (14.94)	$t(39)=2.35$, $p=.025$	SCZ>DPD

Fear	62.85 (21.85)	61.16 (22.65)	68.75 (18.90)	*t*(39)=-.86, p =.394	-
Neutral	75.00 (23.53)	74.11 (23.31)	78.13 (25.66)	*t*(39)=-.42, p =.676	-
AIHQ; Mean (SD)	39.66 (14.27)	41.04 (14.21)	34.71 (14.42)	*t*(39)=1.04, p =.307	-
Hinting Task; Mean (SD)	17.23 (3.12)	17.32 (2.80)	18.71 (1.38)	*t*(39)=-1.61, p =.117	-
TEIS; Mean (SD)	17.08 (4.05)	17.00 (4.27)	16.71 (2.93)	*t*(39)=.26, p =.800	-
Neuropsychological Functioning					
WTAR (estimated FSIQ); Mean (SD)	96.08 (8.94)	95.62 (9.50)	97.79 (6.67)	*t*(39)=-.603, p =.550	-
TMT					
Part A Time (seconds); Mean (SD)	40.59 (16.01)	42.19 (17.53)	32.62 (6.04)	*t*(39)=1.48, p =.147	-
Part B Time (seconds); Mean (SD)	101.28 (39.23	102.23 (41.18)	97.49 (32.67)	*t*(39)=.28, p =.780	-
Mental Flexibility; *Mean (SD)*	61.00 (30.66)	60.03 (31.31)	64.87 (29.89)	*t*(39)=-.37, p =.715	-
Digit Span					
Forward 2E Max; Mean (SD)	5.97 (1.60)	6.00 (1.75)	5.88 (0.99)	*t*(39)=.19, p =.849	-
Backward 2E Max; Mean (SD)	4.03 (1.29)	4.30 (1.33)	3.13 (0.65)	*t*(39)=2.40, p =.022	SCZ>DPD

Table 24 Demographic and clinical characteristics by presence or absence of aggression

Measure	No-Aggression (*N* = 22)	Aggression (*N* = 19)	Group Differences	Direction of Effect
Demographics				
Age; Mean (SD)	40.68 (10.74)	38.74 (11.40)	$t(39)=.56$, $p=.557$	-
Ethnicity *(N)*				
Black British	7	9	$\chi^2(4)=6.53$, $p=.163$	-
White British	10	5		
Black Caribbean	1	4		
Black African	3	0		
Asian	1	1		
Clinical Characteristics				
Diagnosis *(N)*				
Schizophrenia Spectrum Condition	13	10	$\chi^2(2)=2.18$, $p=.336$	-
Dissocial Personality Disorder	6	3		
Comorbid	3	6		
Treatment Length (Years); Mean (SD)	2.75 (1.95)	2.76 (1.52)	$t(39)=-.02$, $p=.981$	-
Chlorpromazine Equivalent Dosage; Mean (SD)	365.91 (172.78)	381.58 (190.18)	$t(39)=-.28$, $p=.784$	-
PCL-R; Mean (SD)	18.09 (7.21)	20.16 (7.48)	$t(39)=-.90$, $p=.374$	-
BPRS; Mean (SD)	46.95 (11.48)	57.47 (12.14)	$t(39)=-2.85$, p =.007	AGG>NAGG
BIS/BAS; Mean (SD)				
Impulsivity	17.55 (4.49)	19.50 (3.58)	$t(39)=-1.44$, p =.159	-
Drive	11.05 (3.33)	12.63 (1.89)	$t(39)=-1.70$, p =.097	-
Fun Seeking	11.18 (3.06)	10.53 (3.72)	$t(39)=.56$, p =.578	-
Reward Responsiveness	16.73 (2.31)	14.88 (4.15)	$t(39)=1.76$, p =.087	-
Social Cognition				
PENN				
Total Correct; Mean (SD)	27.24 (5.77)	26.73 (6.63)	$t(39)=.24$, p =.809	-
Proportion Correct (%)				
Happy	85.71 (19.48)	85.00 (20.70)	$t(39)=.11$, p =.916	-

Sad	72.02 (21.62)	71.67 (20.85)	*t*(39)=.05, p =.961	-
Anger	52.98 (19.73)	52.50 (25.96)	*t*(39)=.06, p =.950	-
Fear	61.31 (21.62)	65.00 (22.76)	*t*(39)=-.49, p =.624	-
Neutral	74.40 (25.46)	75.83 (21.37)	*t*(39)=-.18 p =.860	-
AIHQ; Mean (SD)	37.85 (11.95)	42.67 (17.63)	*t*(39)=-.92, p =.364	-
Hinting; Mean (SD)	18.38 (2.01)	15.50 (3.72)	*t*(39)=2.97, p =.005	NAGG>AGG
TEIS; Mean (SD)	16.77 (3.41)	17.53 (4.94)	*t*(39)=-.56, p =.582	-
Neuropsychological Functioning				
WTAR (estimated FSIQ); Mean (SD)	95.97 (8.19)	96.23 (10.15)	*t*(39)=-.09, p =.933	-
TMT				
Part A Time (seconds); Mean (SD)	37.41 (16.10)	45.26 (15.20)	*t*(39)=-1.49, p =.145	-
Part B Time (seconds); Mean (SD)	95.56 (41.93)	110.96 (33.49)	*t*(39)=-1.13, p =.268	-
Mental Flexibility; *Mean(SD)*	58.16 (33.13)	65.81 (26.52)	*t*(39)=-.71, p =.484	-
Digit Span				
Forward 2E Max; Mean(SD)	5.68 (1.25)	6.31 (1.92)	*t*(39)=-1.16, p =.253	-
Backward 2E Max; Mean(SD)	3.74 (0.87)	4.38 (1.63)	*t*(39)=-1.48, p =.149	-

8.3.2 Relationship with Clinical Characteristics

Four measures were significantly associated with Aggressive Ideation and Isolation (**Table 25**). PCL-R score significantly negatively correlated with Aggressive Ideation. Facial emotion recognition was significantly associated with aggressive ideation, including overall task accuracy and discrimination of specific emotions. Both Aggression Ideation and Isolation were significantly negatively correlated with full-scale IQ, and significantly correlated with performance on Part A of the Trail Making Test. No other statistically significant associations were identified.

Five measures were significantly associated with HRV. PCL-R score significantly negatively correlated with HRV. There was a significant inverse correlation between overall emotion recognition and recognition of fear and HRV. Anger recognition was significantly associated with SDNN and RMSSD only. There was a significant inverse correlation between the Hinting Task and TESI and HRV, and between the AIHQ, SDNN and RMSSD.

BPRS score and performance on Part A of the Trail Making Test were significantly associated with aggression, with PCL-R score showing a significantly negative correlation with aggression. No other measures were statistically significantly associated with aggression.

Table 25 Correlation matrix between clinical characteristics, ESM factors, passive remote monitoring parameters and aggression

Measure	ESM Factors				Passive Remote Monitoring Parameters					Aggression
	Negative Affect	Positive Affect and Social Interactions	Aggressive Ideation	Isolation	Phasic Activity	Tonic Activity	SDNN	RR	RMSSD	
Treatment Length	.15	-.05	-.03	.24	.13	.17	.12	.15	.10	-.05
Chlorpromazine Equivalent	.10	.01	.28	.03	.26	.09	.27	.25	.22	.14
PCL-R Total	-.10	-.09	**-.35***	-.16	.03	.13	**.38***	**.35***	**.36***	-.10
BPRS	.25	-.04	-.04	.04	.08	.11	.19	.12	.16	**.46***
BIS/BAS										
Impulsivity	.36	.03	-.17	.32	.13	.08	.15	.20	.19	.15
Drive	-.06	-.02	-.23	-.17	.24	.16	.09	.12	.18	.21
Fun Seeking	-.04	-.12	-.17	-.30	.10	.14	.20	.19	.13	-.20
Reward Responsiveness	-.13	-.07	.11	-.21	.09	.05	.11	.17	.20	-.27
PENN										
Total Correct	.35	-.01	**.57***	.12	.29	.22	**-.35***	**-.38***	**-.35***	-.11
Proportion Correct										-.11
Happy	.35	-.02	**.55***	.10	.24	.18	-.30	-.29	-.31	-.11
Sad	.33	-.04	**.56***	.13	.20	.21	-.23	-.29	-.26	-.11
Anger	.34	-.01	**.57****	.09	.22	.25	**-.36***	-.25	**-.33***	-.11
Fear	.31	-.02	**.54***	.10	.17	.20	**-.41***	**-.36***	**-.42***	-.11
Neutral	.32	-.03	**.52***	.12	.20	.12	-.29	-.25	-.27	-.11
AIHQ	-.11	-.22	-.12	-.06	.20	.14	**-44***	-.24	**-.32***	.12
Hinting Task	.05	-.21	-.18	.24	.09	.11	**-.37***	**-.40***	**-.35***	**-.59****
TEIS	.10	-.12	-.13	-.09	.20	.15	**-.49***	**-.41***	**-.45***	.03
WTAR FSIQ	-.34	.09	**-.51***	**-.39***	.11	.19	-.11	-.09	-.17	.16
TMT										
Part A	.36	.24	**.44***	**.42***	.24	.20	-.26	-.29	-.18	**.42***
Part B	.11	.04	.03	.29	.08	.10	-.15	-.09	-.11	.27
Mental Flexibility	-.05	-.08	-.20	.16	.26	.19	-.22	-.20	-.23	.14

Digit Span										
Forward 2E Max	-.11	.13	.01	-.06	.03	-.09	-.30	-.22	-.29	-.01
Backward 2E Max	.16	-.14	.11	-.01	-.04	-.06	-.17	-.09	-.11	.14

(*p <.05 ** p<.001)

8.3.3 Relationship with Aggression

Table 26 presents the results of the multilevel models assessing the relationship between the ESM factors, psychophysiological parameters, and aggressive behaviour. In the 20-minute lagged models, physical aggression was significantly predicted by all ESM factors, except isolation, and phasic electrodermal activity. Verbal aggression was significantly predicted by the variables in addition to SDNN, RR and RMSSD. Property aggression was not significantly predicted by any variables. In the 40-minute lagged models both physical and verbal aggression were significantly predicted by all variables except isolation and tonic electrodermal activity. Again, property aggression was not significantly predicted by any variable. In the 60-minute lagged models there were no statistically significant relationships between any predictor variable and aggressive outcome.

Table 27 presents the results of the multilevel models after disaggregating the ESM and passive remote monitoring data by diagnostic group and entering the median split neuropsychological and social cognitive difficulties. Similar to the results in **Table 26**, physical and verbal aggression were significantly predicted by a combination of ESM and passive remote monitoring variables in the 20- and 40-minute lagged models. Isolation was not significantly predictive of any outcome and electrodermal activity was not statistically significant in the 40-minute lagged models. Once again there were no statistically significant findings for property aggression or the 60-minute lagged models.

Table 26 Multilevel models between ESM factors, psychophysiological parameters and aggression

	Outcome Variable	Predictor			95% CI	
			Beta Coefficient (SE)	***p***	**Lower**	**Upper**
20-Minute Lagged Association	**Physical Aggression**	Negative Affect	**.41 (.03)**	***p* =.018**	**.24**	**.58**
		Positive Affect and Social Interaction	**-.39 (.04)**	***p* =.010**	**-.52**	**-.22**
		Aggressive Ideation	**.56 (.02)**	***p* <.001**	**.26**	**.69**
		Isolation	.18 (.03)	*p* =.079	-.05	.26
		Phasic Activity	**.14 (.06)**	***p* =.045**	**.07**	**.21**
		Tonic Activity	.09 (.02)	*p* =.104	-.06	.16
		SDNN	-.10 (.03)	*p* =.184	-.19	.09
		RR	-.08 (.02)	*p* =.140	-.15	.12
		RMSSD	-.05 (.02)	*p* =.229	-.14	.10
	Verbal Aggression	Negative Affect	**.28 (.04)**	***p* =.041**	**.11**	**.39**
		Positive Affect and Social Interaction	**-.19 (.02)**	***p* =.034**	**-.28**	**-.08**
		Aggressive Ideation	**.49 (.02)**	***p* <.001**	**.31**	**.59**
		Isolation	.10 (.03)	*p* =.089	-.05	.19
		Phasic Activity	**.22 (.04)**	***p* =.029**	**.13**	**.35**
		Tonic Activity	.11 (.02)	*p* =.094	-.04	.21
		SDNN	**-.21 (.04)**	***p* =.042**	**-.33**	**-.12**
		RR	**-.18 (.06)**	***p* =.040**	**-.25**	**-.09**
		RMSSD	**-.26 (.03)**	***p* =.039**	**-.34**	**-.17**
	Property Aggression	Negative Affect	-.08 (.02)	*p* =.239	-.20	.18
		Positive Affect and Social Interaction	.11 (.04)	*p* =.327	-.16	.24
		Aggressive Ideation	.16 (.01)	*p* =.098	.09	.20
		Isolation	.04 (.02)	*p* =.184	-.12	.16
		Phasic Activity	-.05 (.03)	*p* =.212	-.09	.17
		Tonic Activity	.09 (.02)	*p* =.257	-.07	.21
		SDNN	.10 (.03)	*p* =.301	-.12	.19
		RR	.05 (.01)	*p* =.350	-.06	.12

		RMSSD	.15 (.03)	*p* =.287	-.04	.23
	Physical Aggression	Negative Affect	**.34 (.07)**	***p* =.042**	**.18**	**.47**
		Positive Affect and Social Interaction	**-.49 (.04)**	***p* =.038**	**-.61**	**-.35**
		Aggressive Ideation	**.59 (.03)**	***p* =.026**	**.41**	**.68**
		Isolation	.22 (.02)	*p* =.081	-.04	.31
		Phasic Activity	**.31 (.04)**	***p* =.036**	**.22**	**.42**
		Tonic Activity	.13 (.05)	*p* =.082	-.09	.20
		SDNN	**-.30 (.03)**	***p* =.027**	**-.42**	**-.21**
		RR	**-.24 (.06)**	***p* =.033**	**-.37**	**-.15**
		RMSSD	**-.21 (.03)**	***p* =.027**	**-.31**	**-.11**
	Verbal Aggression	Negative Affect	**.31 (.04)**	***p* =.030**	**.20**	**.46**
		Positive Affect and Social Interaction	**-.41 (.02)**	***p* =.022**	**-.58**	**-.31**
		Aggressive Ideation	**.36 (.04)**	***p* =.018**	**.23**	**.45**
		Isolation	.12 (.02)	*p* =.109	-.05	.23
		Phasic Activity	**.29 (.04)**	***p* =.028**	**.19**	**.38**
		Tonic Activity	.08 (.03)	*p* =.071	-.06	.16
40-Minute Lagged Association		SDNN	**-.22 (.05)**	***p* =.031**	**-.36**	**-.14**
		RR	**-.20 (.02)**	***p* =.040**	**-.31**	**-.07**
		RMSSD	**-.28 (.06)**	***p* =.036**	**-.40**	**-.13**
	Property Aggression	Negative Affect	-.18 (.03)	*p* =.320	-.25	.09
		Positive Affect and Social Interaction	.10 (.03)	*p* =.421	-.12	.19
		Aggressive Ideation	.19 (.05)	*p* =.393	-.09	.29
		Isolation	.05 (.02)	*p* =.298	-.11	.16
		Phasic Activity	.11 (.04)	*p* =.329	-.06	.23
		Tonic Activity	.05 (.02)	*p* =.406	-.11	.13
		SDNN	.10 (.03)	*p* =.457	-.09	.18
		RR	.12 (.02)	*p* =.391	-.06	.20
		RMSSD	.06 (.02)	*p* =.418	-.11	.16
	Physical Aggression	Negative Affect	.12 (.06)	*p* =.357	-.09	.25
		Positive Affect and Social Interaction	.05 (.02)	*p* =.418	-.10	.13
		Aggressive Ideation	.14 (.03)	*p* =.107	-.06	.23
		Isolation	.03 (.02)	*p* =.520	-.06	.11
60-Minute Lagged Association		Phasic Activity	-.18 (.04)	*p* =.357	-.25	.07

	Tonic Activity	.09 (.03)	*p* =.285	-.16	.19
	SDNN	.15 (.07)	*p* =.396	-.08	.24
	RR	.13 (.04)	*p* =.205	-.18	.26
	RMSSD	.26 (.06)	*p* =.360	-.03	.34
	Negative Affect	.09 (.03)	*p* =.361	-.12	.19
	Positive Affect and Social Interaction	.13 (.03)	*p* =.262	-.05	.23
	Aggressive Ideation	.06 (.02)	*p* =.380	-.11	.18
	Isolation	.10 (.04)	*p* =.325	-.12	.24
Verbal Aggression	Phasic Activity	-.13 (.05)	*p* =.229	-.21	.08
	Tonic Activity	.05 (.02)	*p* =.427	-.09	.13
	SDNN	.15 (.03)	*p* =.504	-.05	.26
	RR	.18 (.04)	*p* =.364	-.08	.34
	RMSSD	.16 (.03)	*p* =.286	-.10	.25
	Negative Affect	.08 (.02)	*p* =.628	-.16	.21
	Positive Affect and Social Interaction	.16 (.06)	*p* =.582	-.06	.28
	Aggressive Ideation	.09 (.05)	*p* =.391	-.12	.18
	Isolation	.13 (.03)	*p* =.229	-.06	.20
Property Aggression	Phasic Activity	-.28 (.12)	*p* =.692	-.38	.04
	Tonic Activity	.16 (.07)	*p* =.575	-.04	.29
	SDNN	.08 (.03)	*p* =.446	-.11	.19
	RR	.10 (.04)	*p* =.329	-.06	.23
	RMSSD	.09 (.02)	*p* =.411	-.12	.19

Table 27 Multilevel models between ESM factors, psychophysiological parameters and aggression (diagnosis and neuropsychological/social cognitive difficulties entered Into model)

	Outcome Variable	Predictor			95% CI	
			Beta Coefficient (SE)	*p*	Lower	Upper
20-Minute Lagged Association	Physical Aggression	Negative Affect	**.34 (.03)**	***p* =.026**	**.25**	**.54**
		Positive Affect and Social Interaction	**-.31 (.05)**	***p* =.033**	**-.47**	**-.18**
		Aggressive Ideation	**.44 (.03)**	***p* <.001**	**.29**	**.52**
		Isolation	.07 (.02)	*p* =.104	-.13	.18
		Phasic Activity	**.19 (.05)**	***p* =.039**	**.09**	**.28**
		Tonic Activity	-.03 (.03)	*p* =.193	-.11	.09
		SDNN	-.06 (.02)	*p* =.229	-.14	.13
		RR	-.03 (.02)	*p* =.257	-.14	.07
		RMSSD	-.09 (.03)	*p* =.312	-.17	.09
	Verbal Aggression	Negative Affect	**.25 (.05)**	***p* =.046**	**.13**	**.34**
		Positive Affect and Social Interaction	**-.22 (.03)**	***p* =.039**	**-.33**	**-.11**
		Aggressive Ideation	**.33 (.03)**	***p* <.001**	**.25**	**.48**
		Isolation	.12 (.02)	*p* =.084	-.02	.21
		Phasic Activity	**.20 (.04)**	***p* =.033**	**.11**	**.32**
		Tonic Activity	.08 (.02)	*p* =.104	-.02	.16
		SDNN	**-.20 (.03)**	***p* =.046**	**-.29**	**-.06**
		RR	**-.24 (.03)**	***p* =.040**	**-.33**	**-.11**
		RMSSD	**-.29 (.02)**	***p* =.042**	**-.37**	**-.14**
	Property Aggression	Negative Affect	-.12 (.03)	*p* =.332	-.21	.11
		Positive Affect and Social Interaction	-.14 (.05)	*p* =.392	-.23	.07
		Aggressive Ideation	.11 (.02)	*p* =.213	-.06	.19
		Isolation	.06 (.03)	*p* =.227	-.09	.14
		Phasic Activity	-.10 (.03)	*p* =.328	-.19	.08
		Tonic Activity	.12 (.03)	*p* =.280	-.05	.20
		SDNN	.08 (.02)	*p* =.465	-.16	.16
		RR	.09 (.02)	*p* =.483	-.14	.17
		RMSSD	.10 (.03)	*p* =.419	-.08	.17

40-Minute Lagged Association	**Physical Aggression**	Negative Affect	**.31 (.05)**	***p* =.046**	**.20**	**.42**
		Positive Affect and Social Interaction	**-.37 (.03)**	***p* =.041**	**-.57**	**-.28**
		Aggressive Ideation	**.52 (.03)**	***p* =.031**	**.33**	**.63**
		Isolation	.17 (.03)	*p* =.098	-.02	.26
		Phasic Activity	.11 (.03)	*p* =.065	-.06	.21
		Tonic Activity	.08 (.04)	*p* =.127	-.10	.19
		SDNN	**-.27 (.03)**	***p* =.037**	**-.39**	**-.14**
		RR	**-.23 (.02)**	***p* =.044**	**-.31**	**-.18**
		RMSSD	**-.20 (.04)**	***p* =.035**	**-.33**	**-.09**
	Verbal Aggression	Negative Affect	**.35 (.03)**	***p* =.036**	**.23**	**.48**
		Positive Affect and Social Interaction	**-.39 (.04)**	***p* =.032**	**-.54**	**-.27**
		Aggressive Ideation	**.27 (.03)**	***p* =.031**	**.17**	**.36**
		Isolation	.10 (.02)	*p* =.171	-.08	.17
		Phasic Activity	.09 (.02)	*p* =.084	-.11	.17
		Tonic Activity	.11 (.03)	*p* =.091	-.04	.19
		SDNN	**-.31 (.04)**	***p* =.040**	**-.41**	**-.14**
		RR	**-.23 (.03)**	***p* =.045**	**-.30**	**-.10**
		RMSSD	**-.20 (.02)**	***p* =.044**	**-.34**	**-.11**
	Property Aggression	Negative Affect	-.11 (.02)	*p* =.408	-.20	.06
		Positive Affect and Social Interaction	.13 (.04)	*p* =.489	-.06	.20
		Aggressive Ideation	.15 (.04)	*p* =.442	-.05	.27
		Isolation	.09 (.02)	*p* =.362	-.10	.17
		Phasic Activity	.07 (.03)	*p* =.383	-.09	.15
		Tonic Activity	.10 (.05)	*p* =.483	-.07	.19
		SDNN	.05 (.02)	*p* =.579	-.11	.14
		RR	.09 (.03)	*p* =.406	-.14	.17
		RMSSD	.10 (.02)	*p* =.462	-.17	.15
60-Minute Lagged Association	**Physical Aggression**	Negative Affect	.10 (.05)	*p* =.410	-.16	.19
		Positive Affect and Social Interaction	-.08 (.03)	*p* =.382	-.14	.11
		Aggressive Ideation	.09 (.03)	*p* =.267	-.08	.15
		Isolation	-.16 (.04)	*p* =.419	-.20	.04
		Phasic Activity	-.06 (.02)	*p* =.492	-.15	.09
		Tonic Activity	.11 (.03)	*p* =.351	-.06	.22

	SDNN	.12 (.03)	*p* =.417	-.07	.20
	RR	.08 (.02)	*p* =.291	-.14	.16
	RMSSD	.07 (.02)	*p* =.397	-.11	.16
	Negative Affect	.12 (.04)	*p* =.427	-.05	.20
	Positive Affect and Social Interaction	.09 (.02)	*p* =.326	-.06	.15
	Aggressive Ideation	-.06 (.02)	*p* =.415	-.19	.06
	Isolation	.07 (.03)	*p* =.393	-.10	.19
Verbal Aggression	Phasic Activity	-.03 (.01)	*p* =.506	-.09	.07
	Tonic Activity	.11 (.03)	*p* =.450	-.05	.18
	SDNN	.14 (.02)	*p* =.516	-.03	.20
	RR	.08 (.03)	*p* =.446	-.11	.16
	RMSSD	.10 (.03)	*p* =.319	-.07	.19
	Negative Affect	.03 (.02)	*p* =.521	-.06	.11
	Positive Affect and Social Interaction	.09 (.04)	*p* =.575	-.15	.16
	Aggressive Ideation	.12 (.03)	*p* =.458	-.09	.17
	Isolation	.11 (.02)	*p* =.392	-.05	.23
Property Aggression	Phasic Activity	-.18 (.05)	*p* =.729	-.27	.02
	Tonic Activity	-.06 (.03)	*p* =.603	-.11	.12
	SDNN	.05 (.02)	*p* =.525	-.04	.11
	RR	.09 (.03)	*p* =.427	-.12	.19
	RMSSD	.07 (.03)	*p* =.493	-.15	.12

8.4 Discussion

To our knowledge this study is the first to use both passive remote monitoring and ESM in an inpatient forensic mental health service to investigate dynamic risk factors for aggressive behaviour. Physical and verbal aggression were significantly predicted by ESM and psychophysiological variables up to 20- and 40-minutes before the observed aggression, partially confirming this study's hypothesis. Increases in negative affect, aggressive ideation, and phasic activity, and decreased positive affect and social interaction and HRV significantly predicted aggression.

Isolation was identified as a significant risk factor for inpatient aggression in the systematic review discussed in Chapter 2 and was therefore included in the ESM protocol, but this factor consistently failed to show a significant relationship with aggression across all the models. One interpretation is that changes in perceived isolation may require longer periods of time to take effect than the timeframe of these models. While social isolation was not predictive of aggression in this sample, this remains an important issue for people with mental health difficulties due to its association with both poorer physical and mental health outcomes (Leigh-Hunt et al., 2017).

While there is generally consistent evidence in non-clinical populations that elevations in EDA correspond to intensity of emotional stimuli (Harley, 2016), as measured experimentally and in naturalistic settings (Andreassi, 2007), there is mixed evidence of how the two components of EDA, phasic and tonic activity, fluctuate in relation to emotional and behavioural experiences in clinical populations. A systematic review reported that while significant phasic EDA hyperactivity has been consistently linked to various emotional experiences, there was inconsistence evidence for these fluctuations with tonic EDA (Sarchiapone et al., 2018). Similarly, in this study phasic EDA was significantly predictive of inpatient aggression across 20- and 40-minute epochs, while tonic EDA consistently failed to show a significant relationship with aggression. This could reflect the relatively slow nature of tonic activity relative to phasic (Boucsein, 1992), suggesting episodic changes in phasic EDA are more informative indicators of episodic changes in risk state. These findings may also suggest the timeframes in this study may not be well-suited to capture this parameter.

The results support neurobiological theories of aggression which propose autonomic deregulation as a contributor to aggressive behaviour (Blake & Grafman, 2004; Siever, 2008), in particular reduced HRV. This may reflect difficulties in downregulating parasympathetic nervous system activity following initial arousal, consistent with previous findings among

individuals with schizophrenia-spectrum conditions (Cella et al., 2018; Montaquila et al., 2015), and supports cross-sectional findings in forensic mental health populations (Puhalla et al., 2019). Studies investigating recovery times for psychophysiological arousal are mixed. For example, manipulation of EDA through cognitive tasks designed to enhance psychophysiological arousal have reported sustained elevations in arousal over a six-minute recovery period compared to baseline (Visnovcova et al., 2016), whereas others have reported a return to baseline arousal within a 10-minute recovery period. Findings from these studies suggest that each epoch in this study could have provided sufficient time for psychophysiological recovery to occur. The lack of statistical significance across the 60-minute epochs suggests that recovery (i.e. returning to a baseline value) may have taken place over this timeframe. However, results suggest that across the 20- and 40-minute epochs recovery did not occur, potentially indicating sustained difficulties in downregulating psychophysiological arousal among participants.

Psychophysiological arousal will naturally fluctuate among individuals over time, but most people will not be aggressive as a result. These findings suggest that participants experienced a heightened vulnerability for aggression during these periods of arousal, potentially influenced by their association with some areas of neuropsychological and social cognitive functioning previously implicated in aggression as illustrated in **Table 27**. Social cognition difficulties have been consistently identified among forensic mental health service users (O'Reilly et al., 2015), but this study is the first to link performance on social cognition measures to HRV in this population. Heart rate variability is a theorised biomarker for social cognition and interactions (Lischke et al., 2018) and these findings suggest that passive remote monitoring may represent an additional method of assessing social cognitive processes during the course of individuals' daily life. Consistent with previous research reporting an interaction between social cognition, cardiac activity, and functional outcomes in individuals with schizophrenia-spectrum conditions (Hamilton et al., 2014), these findings suggest that participants' social cognitive difficulties could exert an important influence on the relationship between psychophysiological deregulation and aggression. Social cognitive functioning could therefore represent a target for treatment and intervention such as cognitive remediation and social cognitive training (Darmedru et al., 2017; Nijman et al., 2020), might reduce an individual's likelihood of aggression.

Previous research suggested that novel technologies and ESM could assist in the prediction of aggression (Ramesh et al., 2018), and these findings may provide a guide as to the

timeframes in which this prediction may be possible. Beyond prediction however, developments in eHealth technology have been accompanied by a growing interest in the potential for just-in-time interventions tailored to individual's changing behaviours and internal state (Nahum-Shani et al., 2018). The blended remote monitoring approach in this study could provide an opportunity for healthcare staff to provide timely support for service users to reduce the likelihood of aggression occurring. In addition, blended remote monitoring could support service users' self-awareness and self-regulation of their psychophysiological and psychological state. For example, modulation of HRV through biofeedback techniques has been associated with a reduction in psychophysiological response to anger-inducing stimuli (Chapman, 2017; Francis et al., 2016).

8.4.1 Strengths and Limitations

Raw passive remote monitoring data requires appropriate filtering to be included in the multilevel models, but a myriad of signal filtering techniques have been developed typically optimised for laboratory research with a significantly smaller amount of (high resolution) psychophysiological data. While the filtering procedures used in this study may not be optimised towards the large volume and lower resolution data produced by blended remote monitoring, these procedures are consistent with previous research and reporting guidelines, and were implemented to ensure a clean signal while minimising data loss.

The multilevel models in this study included four predictors related to the ESM assessments and 5 passive remote monitoring predictors. Previous research which investigated the predictive relationship of the ESM and passive remote monitoring parameters separately reported a similar pattern of findings to these blended models, but these relationships were stronger in the earlier studies presented in Chapters 6 and 7. This might suggest that the number of predictors in these, relative to the sample size, lead to an overfitting of the multilevel models and therefore reduced the strength of the predictive relationships for individual predictors.

8.4.2 Future Directions

Future research could investigate psychophysiological downregulation following aggression, as it is unclear how long the changes reported in this study leading up to aggression would be sustained following an incident, and whether the initial change increases the likelihood of multiple subsequent incidents. This would require research to establish individual baselines in dynamic risk factors investigating the length of time taken to return to this baseline and whether aggression is more likely during this recovery period. This could have important

clinical applications as the recovery period following an act of aggression may be as relevant for assessing risk of future aggression as the initial build up period. Several techniques for establishing baselines in psychophysiological research exist, such as physical rest in a controlled environment or tasks requiring low cognitive load, though there is no consensus as to the optimal technique (Parchment et al., 2016). In addition, establishing suitable baselines for certain parameters may not be achievable, with tonic EDA generating a constantly shifting baseline for example (Boucsein, 2012).

Research to investigate whether the blended remote monitoring data is actionable could be beneficial for service users and staff. For example, it is unclear what level of change in psychophysiological arousal and ESM responses staff would consider necessary to act on, and it is likely that this threshold would be service user specific and reflect relative change in risk factor intensity for the individual. Machine learning approaches could attempt to validate these individual-level thresholds to identify clinically significant patterns of change. Machine learning approaches have been increasingly evaluated in physical and mental healthcare and shown provisional evidence for predicting various outcomes such as hospital readmission (Wiens & Shenoy, 2018) and persistence of depressive symptoms (Hatton et al., 2019). To our knowledge these approaches have not been applied to patterns of psychophysiological arousal.

Future research should also consider the various ethical implications of remote monitoring, such as what interventions may be triggered by changes in psychophysiological arousal and ESM responses and service users' willingness to record information if it meant risking an aversive clinical intervention.

8.5 Chapter Conclusion

The ESM and passive remote monitoring studies reported in Chapters 6 and 7 reported that changes in psychological and psychophysiological risk factors, analysed independently, were significantly associated with increased risk of aggression. This study reported that when these psychological and psychophysiological risk factors were combined these statistically significant relationships with aggression remained. Physical and verbal aggression were predicted by changes in psychophysiological arousal, particularly HRV, aggressive ideation, negative and positive affect and aggressive ideation occurring up to 20- and 40-minutes before the observed aggressive behaviour. However, the strength of the predictive relationship for many of the risk factors was lower than the previous studies, possible reflecting an overfitting of the model. This study therefore highlights future research

opportunities utilising larger sample sizes, to further investigate whether incorporating both passive and ESM data into multilevel model improves their predictive accuracy for aggression. This study also identified that performance on several measures of social cognition were significantly associated with HRV and appeared to influence the relationship between HRV and aggression, consistent with previous research. These findings are consistent with theories linking social cognitive difficulties to increased likelihood of aggression and provides support for targeted interventions to ameliorate these difficulties. There is therefore a potential role of social cognitive difficulties as a marker of psychophysiological deregulation which could be a focus for future research.

Chapter 9 : Thesis Summary

9.1 Overall Aims

Dynamic risk factors are an established component of rehabilitative models in forensic mental health services but are assessed infrequently. This means that there is limited evidence of the extent to which these factors change over short periods of time and the relationship between these changes and aggressive behaviour. Developments in remote monitoring methods such as passive remote monitoring technology and ESM provide an opportunity to investigate short term change in these risk factors. This could offer valuable insights into the frequency and magnitude of short-term fluctuations and their relationship with future aggression. The four empirical studies conducted with staff and service users in a medium secure forensic mental health service were informed by a systematic review. These provide valuable findings suggesting the usefulness of measuring these risk factors and support for the feasibility and acceptability of the remote monitoring methods used. The empirical studies addressed the following key gaps in the literature:

i. **What are staff members' attitudes towards remote monitoring in forensic mental health services?**
ii. **To what extent do dynamic risk factors change over short periods of time?**
iii. **Are short-term changes in dynamic risk factors associated with future aggression?**

9.2 Key Findings

9.2.1 Chapter 2: Systematic Review of Dynamic Risk Factors

This review synthesised the literature on dynamic risk factors for inpatient aggression and identified candidate risk factors for inclusion in the later empirical studies. From a search of 2,385 original studies 74 dynamic risk factors were identified which had statistically significant associations with inpatient aggression with 26 reported by at least two studies. These became the candidate risk factors for the ESM and passive remote monitoring studies later in this thesis. Studies in this literature were often limited by infrequent assessments and a focus on long- rather than short-term aggression, problems that studies reported in this thesis sought to address.

The review addressed several key gaps of previous systematic reviews of inpatient aggression. First, by considering forensic and non-forensic mental health services, as differences between these services could affect risk of aggression, including physical

security, availability of illicit substances and service users' previous contact with the criminal justice system. No risk factors identified were unique to one service, suggesting that the results of the ESM study are applicable to both forensic and non-forensic mental health services.

Second, previous research typically focusses on physical aggression towards others but this review considered the relationship between dynamic risk factors and multiple forms of inpatient aggression. Different types of aggression are encountered in inpatient mental health services and while physical aggression may be the most severe, verbal aggression is more common and costly to manage (Flood et al., 2008). Few risk factors (6%) were associated with only one type of aggression, so those selected for later studies were potentially relevant for the multiple types of aggression encountered in inpatient mental health services.

Third, relationships between individual risk factors and inpatient aggression were investigated independently, rather than the aggregate relationship between multiple risk factors and aggression as is often reported. Previous research has identified individual factors which demonstrate no individual predictive ability for aggression (Coid et al., 2011). It was therefore important to identify and exclude risk factors which did not predict aggression to ensure the studies in this thesis included factors that had a significant predictive relationship with inpatient aggression.

9.2.2 Chapter 3: Qualitative Study of Staff Perspectives

Novel technologies in healthcare are often characterised by non-adoption and poor adherence over time (Greenhalgh et al., 2017). Understanding staff attitudes towards novel healthcare technologies is a critical step to ensuring its uptake and is an essential precondition for delivering benefits (Simblett et al., 2018; Ward et al., 2008). This study was designed to understand these views. Twenty-five staff members took part in five semi-structured focus groups and subsequent member-checking groups confirmed that the recorded findings accurately reflected their views. Five main themes and 18 sub-themes were identified through thematic analysis conducted by independent raters.

One theme exclusively concerned the potential benefits to their current work practices and service user wellbeing. For example, participants reported that many aggressive incidents were not preceded by observable warnings and there were frequently instances where service users could not be easily risk assessed, such as when in their rooms or deliberately

avoiding staff contact. Staff felt that remote monitoring offered an opportunity to understand relevant, but otherwise covert, risk factors for inpatient aggression.

The remaining themes concerned potential barriers to implementation. Data privacy, specifically for third-party access to data and the steps needed to reassure users and staff, and additional workload were important. They also queried the practicalities of how an alert system would be used on the ward. Staff thought that remote monitoring would not appeal or be feasible for all service users but could offer potential benefits for specific subgroups.

Previous studies of novel technologies in forensic mental health services (e.g. Ben-Zeev et al., 2017; de Looff et al., 2019) have failed to take account of staff views. This study confirmed that staff thought that remote monitoring technology in forensic mental health services could provide benefits to assessing and managing risk of aggression, but importantly also identified issues likely to affect initial user engagement and wider implementation. These included some identified in previous research, such as data security and device appearance, representing general considerations for remote monitoring technology use in any setting. But some issues were new, such as using the device as a weapon and integration with existing ward systems and working practices. These may reflect specific considerations relevant to inpatient forensic mental health settings. This study therefore identified relevant issues to consider for later studies in this thesis.

9.2.3 Chapter 4: Pilot Study of Remote Monitoring

Evaluating whether remote monitoring was indeed acceptable to staff and service users was considered an important stage to ensure any barriers to use and potential causes of non-adherence were identified and addressed. This study explored the feasibility and acceptability of two passive remote monitoring devices with both service users and staff, and whether the ESM protocol was acceptable to service users. Thirty-five staff members and six service users wore one of two passive remote monitoring devices for seven consecutive days and completed an end-of-study acceptability questionnaire. The ESM procedure completed by service users consisted of assessments of potential dynamic risk factors identified in the systematic review. The ESM questions were refined through a series of patient and public involvement consultations.

Participants using the Empatica E4 device recorded significantly more hours of valid data than those using the Biovotion device and reported fewer technical difficulties and comfort issues. No participant withdrew because of technical difficulties with the passive remote

monitoring devices. The data processing pipeline was able to identify and successfully handle artefacts within the data. Service user adherence to the ESM protocol surpassed a pre-specified acceptability threshold.

A critical component of user-centred design is to establish through usability testing that novel technologies function as intended without adverse effects (Bastien, 2010), but these processes are typically not reported in relation to novel healthcare technologies (Maramba et al., 2019). While this study did not identify any serious adverse effects from either passive remote monitoring device, quantitative adherence data and qualitative feedback regarding usability and comfort indicated that the Empatica E4 was preferred. In addition, this study reflected a recommendation raised in the staff focus group study that both staff and service users would need to be familiar with the technologies and assessment methods prior to wider use. It is possible that familiarisation and exposure to these remote monitoring methods at this early stage had a positive effect on recruitment and adherence in later studies in this thesis.

9.2.4 Chapter 5: Staff Psychophysiological Variability

An important consideration, but one which is unclear from previous passive remote monitoring research, is what timeframes are optimal for detecting significant change in psychophysiological arousal. This aim of this study was first to investigate the validity of the psychophysiological parameters monitored by the passive remote monitoring device and then to investigate the optimal time periods to identify changes in psychophysiological arousal. Eighteen staff members, half the cohort from the previous study, wore the E4 device for seven consecutive days during their normal waking hours. The relationship between psychophysiological variables was assessed to establish validity. Psychophysiological arousal while participants were on-shift was compared to periods off-shift to confirm that the device was able to accurately identify changes in arousal. These data were then analysed across 20- 40- and 60-minute epochs to establish the optimal timeframes for assessing change in sympathetic and parasympathetic activation.

Electrodermal activity and HRV parameters were significantly intercorrelated and demonstrated validity. Significant differences between on and off shift in both EDA and HRV parameters were identified across 20- and 40-minute epochs, but not 60-minute epochs. These differences reflected autonomic deregulation while on-shift compared to off-shift periods and indicate that the E4 device can accurately capture changes in

psychophysiological arousal, with shorter timeframes being more sensitive to detecting arousal change.

Previous research using passive remote monitoring technology had not established whether sensitivity to detect change is affected by timeframe. For example, de Looff et al. (2019) established change in EDA and heart rate 30-minutes prior to an aggressive event, but did not assess whether these changes could be identified beyond that. Establishing a longer period between psychophysiological changes and onset of aggression could be important in a clinical context as it affords more time for staff to intervene and de-escalate the situation. The reliable change in psychophysiological arousal timeframes are used in later studies to evaluate their relationship with aggression.

9.2.5 Chapter 6: Experience Sampling Study

The results of the systematic review identified dynamic risk factors which shared a statistically significant relationship with inpatient aggression and were considered suitable for monitoring through ESM. This study investigated whether these dynamic risk factors change over short time periods (i.e. minutes and hours) and to investigate whether the changes are significantly associated with future aggression. Forty-one service users in a medium-secure forensic mental health inpatient service participated over seven consecutive days, while staff members rated the occurrence of aggression over the same period. The ESM prompts were broadly similar to those used in the earlier pilot study but were refined through participant feedback.

All dynamic risk factors demonstrated a high degree of within-participant variability at the day and individual prompt level, indicating that these factors do change over short time periods. Observed changes were typically modest and large fluctuations in consecutive ratings were infrequent. Physical and verbal aggression were significantly associated with decreased positive affect and social interactions, and increased aggressive ideation and negative affect up to 20-minutes before the aggressive incident occurred. Property aggression was not significantly associated with any changes, and there were too few incidents of autoaggression to evaluate this reliably.

Previous research investigating change in dynamic risk factors in inpatient settings assesses risk factors infrequently, typically using two assessment periods . As a result these factors have been shown to change over weeks and months (Heffernan et al., 2019), but there has been no evidence of change over shorter periods. This study found that dynamic risk factors

do demonstrate change over minutes and hours. This suggests that assessing these risk factors more frequently could provide a more complete picture of how they fluctuate.

Widely used risk assessments such as the DASA (Ogloff & Daffern, 2006) and HCR-20 (Douglas et al., 2013) feature binary outcomes (i.e. Present/Absent), and cannot take account of intensity. For example, anxiety may be present but not experienced at such a high intensity that it has an impact on risk of aggression. ESM enabled participants to specify not only whether a risk factor was present, but the extent to which it was causing difficulties, therefore providing a more nuanced understanding of both presence and magnitude of change in dynamic risk factors over time.

Enabling service users to self-report their experience of risk factors is also consistent with one of the potential benefits of remote monitoring reported by staff, regarding the *"covert"* nature of some risk factors. Currently risk assessments are completed by staff members whose assessments may not accurately reflect service users' subjective experiences of the risk factors and ratings can be subject to individual biases (Ho et al., 2018). ESM enables participants to convey their account of how they experience risk factors for aggression. A lack of evidence from the perspective of service users was also identified as a limitation of previous research in the systematic review.

The finding that short-term change in dynamic risk factors was associated with inpatient aggression is also a novel contribution to the risk assessment literature. Evidence that change in dynamic risk factors is accompanied by a concordant change in the likelihood of aggression is limited (Heffernan et al., 2019). Overall these findings support the central role that dynamic risk factors have for risk of aggression as set out in theoretical models such as the Risk Need Responsivity model (Andrews, 2012). Evidence from the time-lagged models suggests that the relationship between changes in risk factors and aggression is not instant, which could offer the time for clinical applications.

9.2.6 Chapter 7: Passive Remote Monitoring Study

This study investigated the variability of psychophysiological arousal over short time periods (i.e. minutes and hours) and whether any changes were significantly associated with future aggression. The same participants who took part in the ESM procedure also wore a passive remote monitoring device during waking hours over seven consecutive days, while staff members rated the occurrence of aggression.

Like the findings of the ESM study, all psychophysiological parameters demonstrated a high degree of within-participant variability with EDA demonstrating the largest. Psychophysiological parameters were therefore found to be highly dynamic. Previous research reported autonomic abnormalities among individuals diagnosed with schizophrenia-spectrum conditions and dissocial personality disorder compared to non-affected individuals, therefore differences among participants were examined. Participants with a diagnosis of dissocial personality disorder demonstrated significantly reduced HRV overall compared to participants with schizophrenia-spectrum conditions. Physical and verbal aggression were significantly associated with increased phasic EDA and reduced HRV up to 40-minutes before an aggressive incident occurred. These relationships were not statistically significant in the 60-minute models. In addition, property aggression was not significantly associated with any psychophysiological parameters.

Previous research investigating psychophysiological deregulation and aggression is typically limited to laboratory-based studies, which lack the ecological validity of assessing psychophysiological arousal changes in response to social and environmental stimuli in a participant's daily activities. This cross-sectional approach also limits the opportunity to understand how these changes arise over time. Using passive remote monitoring technology provided a temporally rich assessment of how participants' psychophysiological arousal fluctuated in an inpatient forensic mental health environment, and the extent to which this change was attributable to fluctuations within or between individuals.

To our knowledge only one study has investigated the role of passive remote monitoring technology in a forensic mental health setting (de Looff et al., 2019), and this reported similar findings in relation to EDA and aggression as this study. Increasing EDA was significantly predictive of aggression up to 30-minutes before the incident occurred. These findings advance this timeframe by identifying a significant relationship up to 40-minutes before the incident. The de Loof et al. (2019) study did not investigate HRV parameters, so the current study represents a novel contribution. Short-term fluctuations in HRV demonstrated a relationship to aggression which provides support for the potential contribution of passive remote monitoring technology to understand short-term risk factors for inpatient aggression.

9.2.7 Chapter 8: Blended ESM and Passive Remote Monitoring Study

Chapters 6 and 7 describe psychological and psychophysiological risk factors independently and both had a significant predictive relationship with aggression. The aim of this study was to investigate whether using both types of risk factors increases the predictive accuracy for aggression. In addition, this study investigated the relationship between changes in these risk factors and measures of neuropsychological and social cognitive functioning, areas of functioning which have been associated with aggression in forensic mental health populations. Neuropsychological and social cognitive difficulties may reflect a potential mechanism through which psychophysiological deregulation influences the likelihood of aggression. Understanding the link between these difficulties and psychophysiological deregulation in participant's typical daily environment may therefore identify relevant treatment targets for reducing the risk of aggression.

Findings from this study shared some similarities with those reported in Chapters 6 and 7. For example, property aggression was not significantly predicted by any parameters across either of the three time periods, and no parameter shared a statistically significant relationship with aggression in the 60-minute epoch. In the 20- and 40- epochs statistically significant relationships like those in the previous studies were identified, such as decreasing positive affect and social interactions and decreased HRV. Increasing phasic EDA was significantly associated with aggression in the 40-minute epochs but not in the 20-minute epochs. The strengths of the relationships reported were typically smaller, though still statistically significant, than those reported when the factors where entered separately in the multilevel models. Measures of social cognition were significantly associated with aggressive ideation and negatively correlated with HRV.

This was the first study to investigate blended remote monitoring for inpatient aggression. Theoretical approaches to understanding risk of aggression typically focus on either psychological and behavioural risk factors, or psychophysiological arousal. This study indicated that considering both active self-report and psychophysiological data collected passively may assist in identifying increasing risk of aggression before an incident occurs. While statistically significant findings were identified after including both psychological and psychophysiological parameters together, the overall strength of this relationship was reduced for many parameters compared to the studies reported in Chapters 6 and 7. One explanation could be a potential overfitting of the models due to the number of parameters included in relation to the overall sample size. Future research combining both types of risk

factor into a single model may benefit from larger samples to better understand the impact of this combination on predictive accuracy.

Several measures of social cognition shared a significant relationship with aggressive ideation and HRV, which is consistent with previous research linking social cognitive difficulties to aggression in forensic mental health populations (Ahmed et al., 2018). Whereas previous research investigated this relationship cross-sectionally through laboratory-based assessments, this study was able to investigate this link in the context of participants' typical daily environment and activities. The findings therefore reinforce the importance of social cognitive difficulties when considering risk of aggression in this population, as these difficulties appear to exert an influence on the relationship between psychological and psychophysiological risk factors with aggression.

9.3 Interpretation and Clinical Implications

9.3.1 Theoretical Importance of Dynamic Risk Factors

Dynamic risk factors have been a central tenet of leading models of rehabilitation in forensic mental health services (Andrews, 2012), but methodological limitations of previous research, specifically infrequent assessments, has limited the understanding of their relevance for assessing short-term changes in risk state and therefore preventing aggression (Heffernan et al., 2019). Previous evidence has only established change over periods of weeks and months, but this offers little benefit for staff members seeking to understand moment-to-moment changes in their service users' risk state. This thesis provides novel evidence of the capacity of dynamic risk factors to change over periods of minutes and hours, confirming their relevance to short term risk state change.

Findings from the passive and blended remote monitoring studies support neurophysiological theories linking autonomic deregulation to aggressive behaviour (Siever, 2008), with participants demonstrating significant fluctuations in EDA and HRV parameters. These fluctuations reflected patterns of psychophysiological hyperarousal associated with reactive and impulsive forms of aggression (Scarpa & Raine, 2000), which may also reflect the higher proportion of participants with a schizophrenia-spectrum condition relative to DPD that hyperarousal is associated with. In addition to psychophysiological hyperarousal participants also experienced difficulties downregulating psychophysiological arousal, which differed from previous studies which have identified faster downregulation of EDA and HRV than observed in participants in this study. While in need of further investigation and

replication, participants may experience significant difficulties downregulating psychophysiological arousal contributing to the propensity for aggression.

In addition to being associated with change in risk state and aggressive behaviour, dynamic risk factors are theorised to represent valuable treatment targets to prevent aggression occurring (Douglas & Skeem, 2005). Evaluating the effect of targeted treatment on the occurrence of aggression was beyond the scope of this thesis and would help to clarify whether a causal relationship exists between dynamic risk factors and aggression. However, these findings do contribute an understanding of how these treatment goals may be achieved. For example, risk assessments and targeted interventions for dynamic risk factors are typically staff-initiated and may be administered without service users' consent, such as medication and seclusion. However, the findings of the staff focus groups suggest that remote monitoring could be promoted by staff as a way of enabling service users themselves to take an active role in recognising and reporting their own experiences of how their risk factors fluctuate. Individualised behavioural interventions designed to support service users through periods of high emotional arousal are already routinely used within inpatient services (e.g. access to a garden space, one-to-one sessions with primary nurses), though the staff reports from the earlier focus groups suggest that these can sometimes occur too late. Earlier awareness of increasing physiological arousal through remote monitoring technology may facilitate earlier use of these effective means of support.

Remote monitoring could also enable novel intervention approaches such as biofeedback, providing objective and in-the-moment evidence to service users of how their levels of arousal appear to be changing (Peira et al., 2013). While biofeedback interventions have seen limited use in relation to anger and aggression, preliminary evidence from intervention studies in non-clinical populations report significant reductions in the intensity of aggressive ideation and incidents of aggression (Francis et al., 2016; Hillman & Chapman, 2018).

Future research is required to investigate the potential benefits of biofeedback for individuals using inpatient forensic mental health services . In addition, the context of the psychophysiological deregulation is important to consider for any intervention based on these data. For example, as reported in this thesis, increasing EDA may reflect an increasing likelihood of aggression, but could also reflect excitement about a forthcoming family visit or happiness about a transition to ward of lower security. Future research evaluating the efficacy of a psychophysiological-informed intervention could therefore investigate the

relevance and necessity of the intervention from service users' perspectives to understand whether the intervention was justified or in response psychophysiological arousal triggered by factors not associated with risk of aggression (i.e. a false alarm). The remote monitoring methods used in this thesis also required a higher level of sustained service users engagement than existing risk assessments, suggesting that any future role of these methods in assessing and managing inpatient aggression may involve a balance between individual workload and intrusion and clinical benefit (Large & Nielssen, 2017).

9.3.2 Balancing Risk and Protective Factors

This thesis contributes to the extensive literature surrounding risk factors for inpatient aggression, but protective factors have received comparatively less research attention (de Vries Robbé et al., 2016). Protective factors refer to personal strengths and resources which reduce the likelihood of aggression (de Ruiter & Nicholls, 2011) and reflect a strength-based approach which confers additional benefits to approaches which focus solely of risk (Neves et al., 2019). For example, pure risk-orientated approaches can lead to biased and overexaggerated perceptions of risk (Webster et al., 2009) and are considered unfair by service users (Gagliardi et al., 2004). Considering protective factors also helps staff and clinicians to build therapeutic alliance with service users and provides a clear treatment focus to enhance individual strengths (de Vries Robbé et al., 2012). The value added by strength-based approaches which consider protective factors is reflected in risk assessment instruments such as the SAPROF which feature a balance of risk and protective factors (de Vogel et al., 2012), in addition to theoretical models such as the Good Lives Model (Ward et al., 2007).

Findings from both the ESM and blended remote monitoring studies indicate increased positive affect and social interactions may function as protective factors and limit the likelihood of inpatient aggression. Enhancing these factors and guarding against significant reductions in positive affect and social interactions could therefore protect against the risk of aggression and represent valuable treatment targets. These are already acknowledged as an important component of recovery-orientated care, given the challenging interpersonal relationships that can exist in inpatient services (Serran & Marshall, 2010). The typically long periods of inpatient treatment within forensic mental health services may offer a good opportunity to build the positive collaborative relationships that are vital for successful service user outcomes.

9.3.3 'Nothing for Us Without Us' - Service Users' Contribution to Risk Assessments

Actively involving service users in discussions and decisions about their care is an integral component of recovery in forensic mental health services (Drennan & Alred, 2013), but existing risk assessments are rated and interpreted solely by staff members. The systematic review identified no studies which evaluated service users' views about their own risk factors for aggression. Previous reviews also indicate that service user involvement in the development and evaluation of forensic mental health services more broadly is limited (MacInnes et al., 2011). Faulkner (2007) reported that while challenges to achieving effective service user engagement exist, it can provide a range of benefits for both staff and service users. For example, service user engagement can benefit the interpretation and accessibility of information provided to service users such as clinical reports.

In this thesis service users made an active contribution to the overall project in several important ways. ***Advice and support*** were gained from service users within the recruitment site and from those external to the site as part of consultations with experts by experience research advisory groups. This advice and support occurred from the outset during the research design phase, identifying relevant areas of investigation and potential barriers. This input continued throughout the development phase of the project, with a key area of input being the ***identification and interpretation*** of the selected risk factors for the ESM procedure, and ***usability*** considerations for the remote monitoring procedure and device selection. ESM self-reports will not substitute for assessments conducted by staff, whose understanding of the service users under their care forms the core principle of relational security (Chester et al., 2017), but could serve as an adjunct emphasising valuable subjective experiences that would otherwise not be obtained through informant-report measures. Ensuring service user perspectives are sought as part of risk assessment procedures may improve the ability to detect relevant changes in risk state, in addition to highlighting treatment targets considered relevant by service users. A principle of service user engagement in risk assessments may also provide a broader sense of active participation in decisions made about their care.

9.3.4 Acceptability and Adoption

The proliferation of novel healthcare technologies and systems in recent years has not been accompanied by widespread uptake (Greenhalgh & Papoutsi, 2019). For example, single-site service evaluations of new systems such as remote location tracking (Tully et al., 2016) and

motion detectors (Tully et al., 2015) have yet to see widespread adoption by the wider network of forensic mental health services. Reasons for this are varied and include a lack of end-user training and familiarity with novel technologies, infrastructure barriers within services, resistance to new technology, and a lack of evidence of the relevance and effectiveness of the technology. These issues highlight the importance of involving end-users in the development and implementation of novel healthcare technologies (Velthoven & Cordon, 2019). Service users and staff were consulted in the initial planning stages of this thesis, followed up by a qualitative study with staff members, which indicated that remote monitoring for inpatient aggression had the potential to support current working practices and improve service users' experience of inpatient care.

An additional reason for the lack of widespread adoption of novel healthcare technologies is the failure to take sufficient account of the overall complexity of disseminating innovation across the health service (Greenhalgh et al., 2017). Findings from the staff focus groups illustrate that there are a multitude of issues that would need to be considered by larger-scale multisite studies before widespread use of remote monitoring technology for inpatient aggression could be considered. These include considerations of how the remote monitoring data could integrate with existing work practices and digital systems, and the specific role of the remote monitoring technology within services. The thesis findings suggest this role could be multifaceted, including identifying heightened periods where aggression may be more likely, and routine monitoring of risk factors. Identifying the roles that remote monitoring may play within services, and how these may support existing practices, is critical for effective implementation. Medicolegal considerations around data security and access represent another central issue for widespread use of remote monitoring. Careful consideration needs to be given to issues of where user data is stored and who can access this data, particularly given recent developments in data protection legislation in the UK through GDPR.

9.4 Strengths, Limitations and Future Research Directions

This thesis represents the first research conducted using both ESM and remote monitoring technology within forensic mental health services. These results would benefit from replication to investigate their generalisability to other forensic and non-forensic mental health settings and populations where aggression occurs. This includes both the data of service users and staff, as the results of the qualitative focus groups in this thesis represent

the views of a relatively small number of staff from one particular service and may not necessarily reflect those of the wider forensic mental health workforce.

This thesis established that dynamic risk factors can change over short periods of time in inpatient settings but was not able to establish what caused these changes. Previous research has attributed positive change in risk factors, measured over periods of weeks and months, to psychopharmacological and psychological therapy (Beggs, 2010; Kingston & Olver, 2018), though there is debate as to the precise mechanisms underlying these changes (Kroner & Yessine, 2013). It is unclear to what extent participants' treatment engagement could produce the observed changes in risk factors during the relatively short time periods in this thesis, though there is evidence from the non-forensic mental health literature of immediate post-treatment changes in factors such as affect (Grant et al., 2018; Mcclintock et al., 2016).

Future research could seek to investigate any post treatment changes in service users' risk factors to establish the speed at which treatment produces change. A high proportion (90.2%) of participants in this thesis received pharmacological and/or psychological therapy and future studies could examine patterns of change in risk factors in relation to issues such as perceived quality of treatment, stage of treatment and monotherapy vs combination therapy. This may highlight specific mechanisms through which treatment might exert an influence of participants' risk factors. Longitudinal assessments would also be a valuable method for establishing long-term change in risk factors following treatment, though would be dependent on long-term participant acceptability of remote monitoring.

The aggression measure adopted in this thesis has been widely used in previous research, has good inter-rater reliability and correlates with other aggression measures (Steinert et al., 2000). However, underreporting, particularly of verbal aggression, is a persistent limitation (Chan & Chow, 2014). For example, previous studies using staff-report measures have shown that up to 45% of incidents in inpatient services go unreported (Hvidhjelm et al., 2014). In the studies in this thesis accurately capturing aggressive incidents was ensured by extracting information from the service's electronic records system as an adjunct to staff ratings. Using both approaches should enhance the reliability of incidents recordings compared to previous research which has relied on either staff-report measures or hospital records.

A limitation of previous research has been its use of dichotomous measures of risk factors which ignore the fact that these factors exist on a continuum of individual experience (Coid et al., 2013; Ullrich et al., 2018). Chapters 6 and 7 for example, established that the risk factors were not static within individual participants, therefore it would have been inappropriate to measure these though a dichotomous measure. The remote monitoring approach employed is an important strength for two key reasons. First, employing repeated short-term assessments of risk factors provides an opportunity to investigate a dose-response relationship between risk factors and aggression (Wooditch et al., 2013). This understanding will have practical implications as it would highlight relevant treatment targets to reduce the likelihood of aggression, which is the central tenet of the need principle with the Risk Need Responsivity model.

The dynamic nature of these risk factors means that some may no longer exert a significant influence by the time aggression occurs (Ullrich et al., 2014). **Figure 28** illustrates the limitation of single time point assessments. In this example an initially low level of negative affect measured at one time point increases considerably during the period between initial onset and the eventual aggressive outcome, to the point where it may be an important contributor to that outcome and treatment target. With only one time point, however, this increase will be missed, and may be regarded as irrelevant. **Figure 29** illustrates the advantages offered by a continuous monitoring method, in which increased negative affect is detected through the multiple assessments.

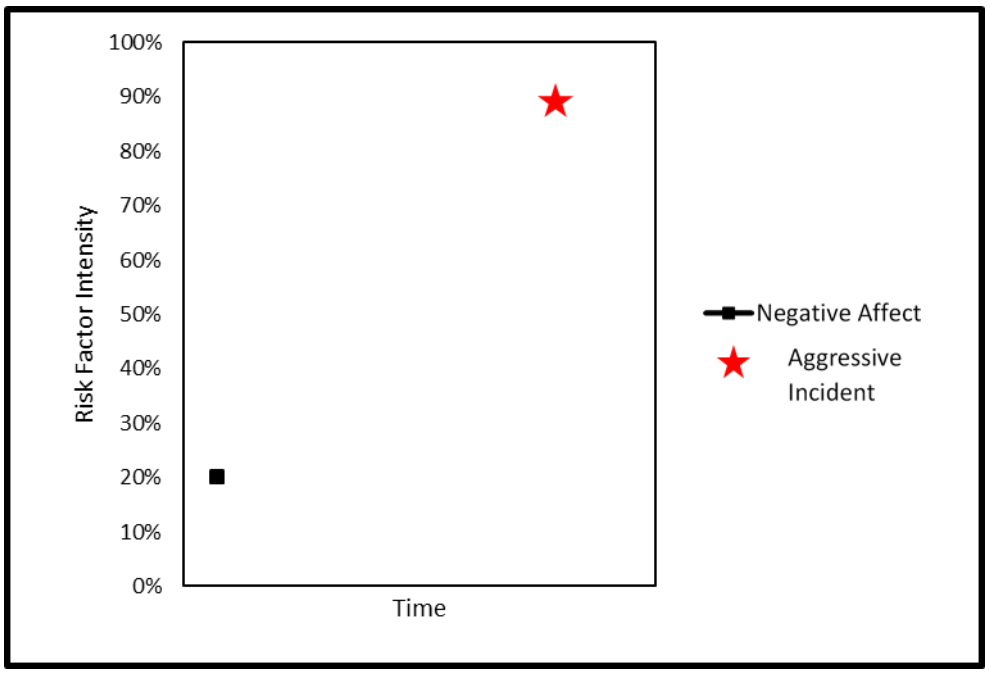

Figure 28 Single time-point assessment of negative affect failing to identify its increasing relevance to the aggressive outcome over time.

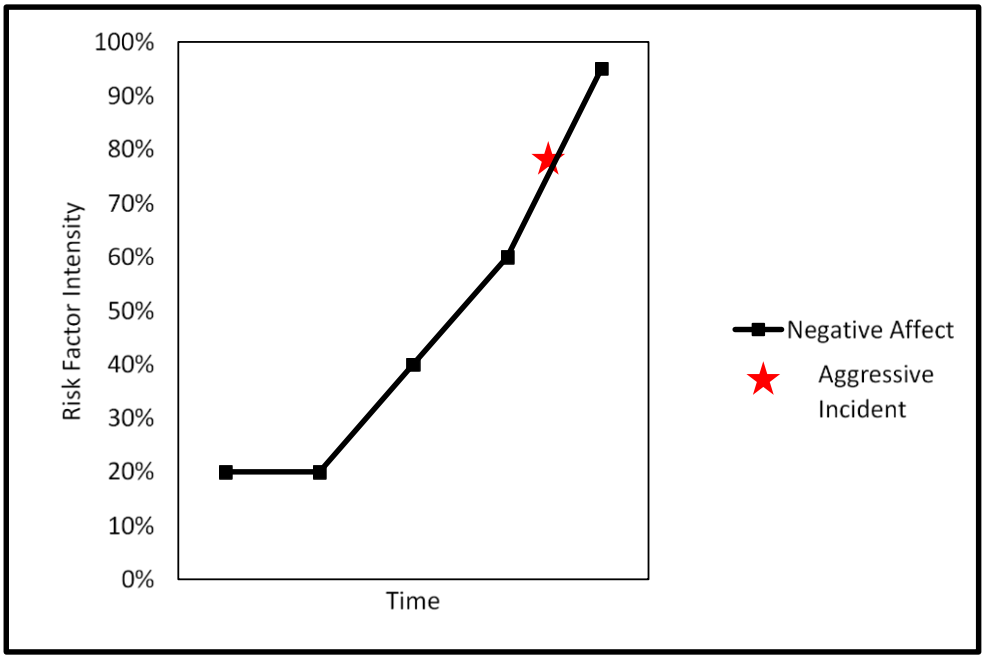

Figure 29 Multiple timepoint assessment of negative affect enabling an understanding of its increasing relevance to the aggressive outcome over time

Another important strength of the continuum approach is that it established a temporal relationship between risk factors and aggression (i.e. that changes in risk factors are observed before the aggressive incident). The findings from the ESM, passive remote

monitoring and blended remote monitoring studies indicated that these changes related to a variety of factors. These included changes in positive affect and social interactions, negative affect, aggressive ideation, and psychophysiological arousal. There is considerable debate over whether dynamic risk factors have a causal relationship with aggression (Ward, 2016), with temporal proximity representing a key criterion for establishing causal relationships (Hill, 1965). This relationship has important theoretical implications, but temporal proximity does not necessarily entail a causal relationship (Ullrich et al., 2018) as pathways from dynamic risk factors to aggression may not be direct. For example, the relationship between changes in dynamic risk factors and aggression may be influenced by social cognitive difficulties, as reported in the blended remote monitoring study, and the presence of static factors as suggested in previous research (Ramesh et al., 2018) (see **Figure 30**). We therefore need research that examines the contribution played by static risk factors as potential moderators or mediators of dynamic risk factors and aggression. This type of research will also establish whether dynamic risk factors meet the additional criteria for a causal relationship, such as a dose-response relationship discussed above.

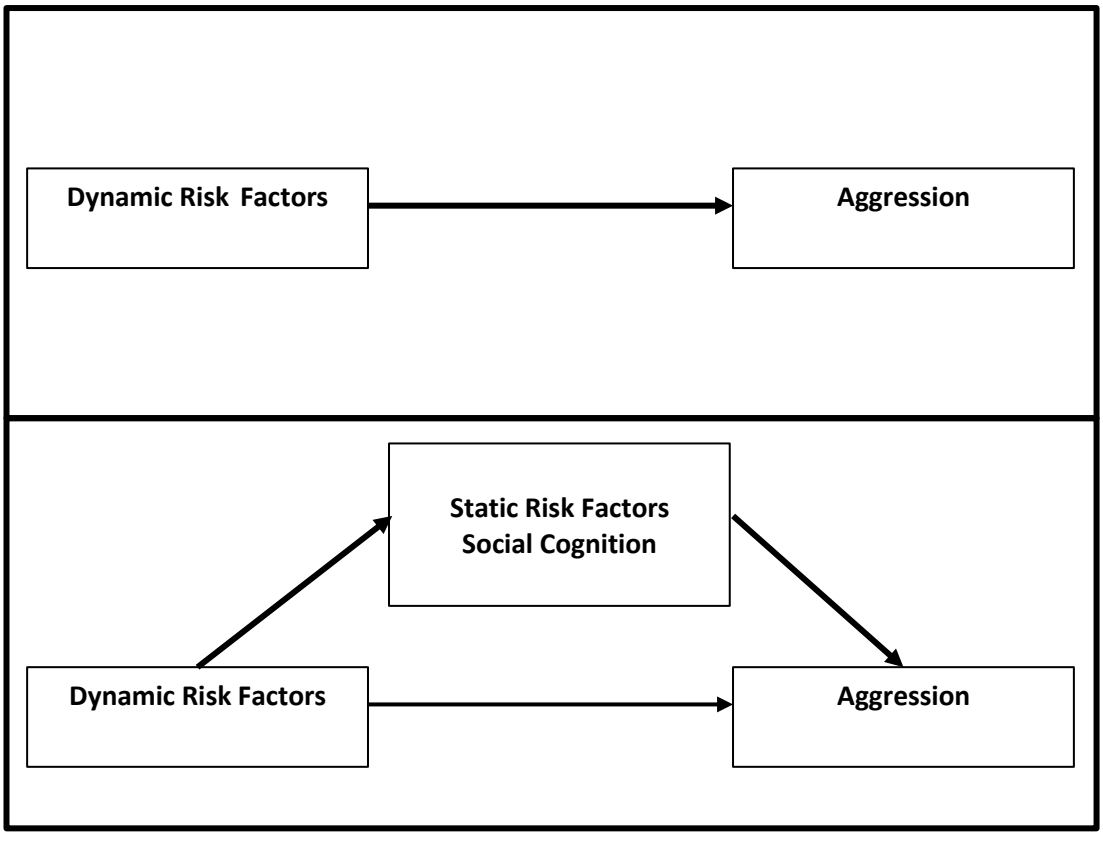

Figure 30 Direct and indirect relationship between dynamic risk factors and aggression

Traditional risk assessments do not enable the service user themselves to report which risk factors may be most relevant for them (Chan et al., 2016; Mulder et al., 2016). While an

important strength of these studies was the inclusion of repeated short-term ratings enabling participants to report their individual experience of these risk factors, future research could explore the utility of enabling service users to report their own risk factors, in addition to a set of general factors. For example, the ESM procedure could be modified to include free-text response sections, enabling participants to highlight factors that they feel are important to their own risk of aggression, but which were not currently captured. This would represent a move away from broad brush quantitative risk assessment towards an individualised understanding of the difficulties experienced and opportunities for support which is consistent with the strength-based approach discussed earlier.

Aggressive incidents were rated by staff members who were blind to the remote monitoring data reported by participants. Staff members' ratings could therefore not be influenced by an awareness of the dynamic risk factors. Previous research typically employs staff members to act as raters for both predictors of aggression and aggressive outcomes, which introduces potential issues of rater bias (van de Sande et al., 2011). Adequate blinding is not always practical with staff raters but can be achieved by asking service users to act as their own raters as illustrated in this thesis.

The studies were conducted in a medium secure service in which all service users were men, therefore these findings may not be generalisable to women. This is a limitation shared by a large body of the risk assessment literature (de Vogel et al., 2019; Gower et al., 2020) and represents an important area for future research. Although men are the majority in forensic services, the 13% women in the forensic mental health population in the UK (Rutherford & Duggan, 2008) should not be ignored. Evidence on risk factors and outcomes for women is very limited. (Somers & Bartlett, 2014) so similar studies to those in this thesis targeting women would fill an important gap. The results could have clinical implications for gender-specific assessment and management approaches, such as weighting specific risk factors differently between men and women (Skeem et al., 2005). The generalisability of the prediction modelling and machine learning findings is affected by a failure to account for differences across ethnic groups (Robinson et al., 2020). For example, previous research has demonstrated significant variations in parasympathetic activity among African Americans compared to European Americans (Hill et al., 2015). The studies reported in this thesis did not identify any statistically significant differences in the relationship between risk factors and aggression according to ethnicity, but exploring potential differences in future research is an important consideration which may lead to more tailored treatment and management

approaches. Tailoring these approaches is particularly important due to the range of others variables which can influence activity of the autonomic nervous system, such as metabolism (Licht et al., 2013) and natural autonomic reactivity (Stange et al., 2017), which may limit the generalisability of approaches across individuals.

An average of 2.9 aggressive incidents per day were recorded during this thesis which is comparable to previous research and is a low base rate. Only two incidents of autoaggression were recorded which prevents reliable use of this information in statistical analysis. Increasing the period of data collection to capture more incidents would enhance power for the statistics (Abidin et al., 2013a) and machine learning. Understanding the feasibility and acceptability of remote monitoring beyond the seven-day period reported in this thesis and what factors might enhance engagement for widespread roll-out is important. For example, design-characteristics of remote monitoring technology, such as gamification elements and interactive user-feedback, and perceiving a benefit may contribute to sustained user-engagement (Simblett et al., 2018). Alternative settings such as acute and first episode psychosis services, where rates of aggression can be higher would also aid machine learning although these services cover different populations (Coid et al., 2013; Ullrich et al., 2014).

Establishing when incidents occurred is also important for the accuracy of the time-lagged models reported in Chapters 6, 7 and 8. Hospital policy encourages staff members to record aggressive incidents as soon as is practical, however future research could consider the timestamp feature of many modern passive remote monitoring devices to enable staff to record the onset of an aggressive incident in-the-moment. This was not practical in this thesis due to the limited availability of devices for both staff and service users, and a desire to ensure that there was no increase in staff workload (a decision made in response to discussions in the staff focus groups).

Novel technological developments are ubiquitous in modern society and mental healthcare is no exception. Significant discussion and research attention is being directed towards how developments in areas such as digital phenotyping (Henson et al., 2020), mobile applications (Huckvale et al., 2020) and passive remote monitoring technology (Resnick & Appelbaum, 2019) might support the work of mental health services in promoting the health and wellbeing of service users. These developments show no sign of abating, but nor have they yet demonstrated significant clinical benefit for the population for which they were designed and/or widespread uptake and implementation. Critically analysing the value of

technological developments for supporting the health and wellbeing of service users should be a central goal for future research.

9.5 Conclusion

The findings reported here contributed to our knowledge of dynamic risk factors for inpatient aggression. Dynamic risk factors, both psychological and psychophysiological, demonstrated substantial change over significantly shorter periods of time than identified in previous research. This suggests that typical approaches to risk assessment which conduct assessments over days and weeks are liable to miss these short-term changes, and subsequently misinterpret an individuals' risk state. The findings also highlight potentially valuable treatment targets including service users' social interactions within services and periods of shifting mood state. They raise interesting possibilities for novel biofeedback interventions addressing individuals' changes in psychophysiological arousal. These may be supported by the evident staff interest in remote monitoring approaches to support care which was identified in the early study in this thesis. Key opportunities for future research relate to clinical issues, such as whether targeted interventions addressing these risk factors can reduce the likelihood of aggression occurring; medicolegal considerations around the collection, access and use of individual data through remote monitoring technology; and technical developments in available technology, data filtering and analysis approaches.

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Appendices

11.1 Appendix 1- All dynamic risk factors investigated in included studies

Study	Aggression Frequency	Results
Abidin et al. (2013)	Physically aggressive incidents: 13 Autoaggressive incidents: 7	Physical aggression was predicted by: Sixteen START items: social skills (AUC = .76, *p* = .003), relationships (AUC = .77, *p* = .002), occupational difficulties (AUC = .69, *p* = .031), recreational (AUC = .73, *p* = .007), self-care (AUC = .71, *p* = .014), emotional state (AUC = .73, *p* = .007), substance use (AUC = .68, *p* = .040), impulse control (AUC = .80, *p* = .001), external triggers (AUC = .78, *p* = .001), social support (AUC = .70, *p* = .021), attitudes (AUC = .78, *p* = .001), rule adherence (AUC = .76, *p* = .002), conduct (AUC = .81, *p* = .001), plans (AUC = .69, *p* = .030), coping (AUC = .69, *p* = .031), and treatability (AUC = .76, *p* = .003). **F**our items were not statistically significant: mental state, material resources, medication adherence, and insight (*p*s > .08). Six HCR-20 items: negative attitudes (AUC = .77, *p* = .002), impulsivity (AUC = .74, *p* = .005), unresponsiveness to treatment (AUC = .75, *p* = .005), plans lacking feasibility (AUC = .69, *p* = .030), non-compliance with remediation attempts (AUC = .76, *p* = .003), and stress (AUC = .74, *p* = .005). Four items were not statistically significant: lack of insight, active symptoms of major mental illness, exposure to destabilisers, and lack of personal support (*p*s > .05). Two S-RAMM items: psychological symptoms (AUC = .67, *p* = .047), and problem-solving deficits (AUC = .74, *p* = .006). Eleven items were not statistically significant: suicidal ideation, hopelessness, treatment adherence, substance use, psychiatric admission and discharge, psychosocial stress, access to method of suicide, future service contact, future response to drug treatment, future response to psychological intervention, and future stress (*p*s > .09). Six DUNDRUM-3 items: physical health (AUC = .69, *p* = .033), mental health (AUC = .80, *p* = .001), drugs and alcohol (AUC = .77, *p* = .002), self-care (AUC = .75, *p* = .005), education, occupation, and creativity (AUC = .82, *p* = .001), and family and social networks (AUC = .70, *p* = .027). One item (problem behaviours) was not statistically significant (*p* = .072). One DUNDRUM-4 item: stability (AUC = .77, *p* = .003). Four items were not statistically significant: insight, rapport and working alliance, leave, and victim sensitivity issues (*p*s > .05). Autoaggression was predicted by: One START item: mental state (AUC = .73, *p* = .045). The remaining 19 items were not statistically significant (*p*s > .06) Three HCR-20 items: negatives attitudes (AUC = .75, *p* = .027), being unresponsive to treatment (AUC = .79, *p* = .010), and stress (AUC = .74, *p* = .039). The remaining seven items were not statistically significant (*p*s > .05). Two S-RAMM items: psychological symptoms (AUC = .75, *p* = .031), problem solving deficits (AUC = .76, *p* = .022). The remaining 11 items were not statistically significant (*p*s > .05). Two DUNDRUM-3 items: mental health (AUC = .80, *p* = .008), and education, occupation, and creativity (AUC = .78, *p* = .016). The remaining 5 items were not statistically significant (*p*s > .07). One DUNDRUM-4 item: stability (AUC = .76, *p* = .022). The remaining 4 items were not statistically significant (*p*s > .08).

Bjorkdahl et al. (2006)	Physically aggressive incidents: 18	Risk of physical aggression was significantly increased by confusion (HR = 3.38, p = .013), irritability (HR = 6.27, p <.001), boisterousness (HR = 5.04, p = .007), and verbal threats (HR = 3, p <.001). One item (physical threats) was not statistically significant (p = .30).
Brewer et al. (2016)	Not reported	Verbal, physical, property, and autoaggression were significantly associated with all eight SDRS items: responsibility, coping skills, anxiety, anger, or frustration, loss of temper, consideration of others, poor housekeeping, and poor self-care (ps <.05). Verbal aggression was significantly associated with seven START items: mental state (r_s = -.236, p <.001), substance use (r_s = -.287, p <.001), attitudes (r_s = -.147, p <.05), medication adherence (r_s = -.322, p <.001), conduct (r_s = .209, p <.001), insight (r_s = -.174, p <.001), and treatability (r_s = -.128, p <.05). Five items were not statistically significant: emotional state, impulse control, external triggers, rule adherence, and coping (ps >.05). Physical aggression was significantly associated with six START items: mental state (r_s = -0.248, p <.001), substance use (r_s = -0.334, p <.001), attitudes (r_s = -0.156, p <.05), medication adherence (r_s = -0.349, p <.001), rule adherence (r_s = -0.183, p <.001), and insight (r_s = -0.161, p <.05). Six START items were not statistically significant (ps >.05). Property aggression was significantly associated with seven START items: mental state (r_s = -0.148, p <.05), emotional state (r_s = 0.143, p <.05), substance use (r_s = -0.291, p <.001), attitudes (r_s = -0.194, p <.001), medication adherence (r_s = -0.219, p <.001), conduct (r_s = 0.151, p <.05), and coping (r_s = 0.170, p <.001). Five items were not statistically significant. Autoaggression was significantly associated with four START items: substance use (r_s = -0.179, p <.001), attitudes (r_s = -0.236, p <.001), insight (r_s = -0.132, p <.05), and coping (r_s = 0.126, p <.05). Eight items were not statistically significant (ps >.05).
Brugman et al. (2016)	All aggressive incidents: 89	Verbal aggression was significantly associated with attentional bias towards threat (β = .002, p <.01) and aggression (β = .001, p <.05), emotion recognition deficits for sadness at 40% (β = -.042, p <.05) 70% (β = .075, p <.01) and 100% intensity (β = -.061, p <.05), and emotion recognition deficits for happiness at 40% intensity (β = .032, p <.05). Vigilance for threatening stimuli, implicit associations with violence, emotion recognition deficits for anxiety, anger, surprise, and disgust, and response inhibition were not statistically significant (ps >.05). Physical aggression was significantly associated with decreased response inhibition (β = -.015, p <.01). Attentional bias, vigilance for threatening stimuli, implicit associations with violence, and emotion recognition deficits were not statistically significant. Property aggression was significantly associated with emotion recognition deficits for anger at 40% intensity (β = .010, p <.01) but not 70% intensity (p >.05). Attentional bias, vigilance for threatening stimuli, implicit associations with violence, emotion recognition deficits for anxiety, sadness, happiness, surprise, and disgust, and response inhibition were not statistically significant (ps >.05).

de Looff et al. (2019)	Physically aggressive incidents: 5 Verbally aggressive incidents: 78 Property aggression incidents: 22 Autoaggressive incidents: 9	Significant increases, compared to individual baselines, were observed in electrodermal activity (p <.05) and heart rate (p <.05) 20 minutes prior to observable aggressive behaviour.
Grevatt et al. (2004)	Physically aggressive incidents:13 Verbally aggressive incidents: 17 Property aggression incidents: 9	Participants who had aggressive incidents scored significantly higher for lack of insight (p = .010) and active signs of major mental illness (p = .017) than those who did not have aggressive incidents. The following items were not statistically significant (ps >.05): HCR-20: negative attitudes, impulsivity, and unresponsive to treatment. VRS: violent lifestyle, criminal personality, criminal attitudes, work ethic, criminal peers, interpersonal aggression, emotional control, weapon use, insight into violence, mental disorder, substance abuse, stability of relationships with significant others, impulsivity, and cognitive distortion.
Kelly et al. (2015)	Physically aggressive incidents: 244	Frequency of physical assaults was significantly associated with patient-staff conflict (r = 0.54, p <.001), and staff-staff conflict (r = 0.21, p <.001). Stress reactivity to social conflict significantly moderated the relationship between physical assaults and staff-staff conflict (r = -0.16, p <.01).

Linaker & Busch-Iversen (1995)	Physically aggressive incidents: 48	Confusion (χ^2 = 13.06, p <.01), irritability (χ^2 = 11.85, p <.01), boisterousness (χ^2 = 7.35, p <.05), physical threats (χ^2 = 28.45, p <.001), verbal threats (χ^2 = 28.49, p <.001), and attacks against objects (χ^2 = 24.02, p <.001) were significantly more frequent 24-hours prior to a physically aggressive incident, compared to a control period two weeks prior.
Lindsay et al. (2004)	Physically aggressive incidents: 18	Significant differences in mood (f= 72.69, p <.01), antisocial behaviour (f= 74.79, p <.01), and aberrant thoughts (f= 22.86, p <.01) were reported between the day of the aggressive incident, the day prior to the incident, and a control period at least seven days prior. Bonferroni corrections indicated significant differences in these risk factors between the day of the aggressive incident and the control period. Self-regulation, therapeutic alliance, and compliance with routine were not statistically significant (p >.05).
McDermott et al. (2008)	Physical aggression: .28 (SD = .64)[a]	Physically aggressive incidents overall were predicted by positive psychotic symptoms (AUC = .64, p ≤.05), hostility (AUC = .66, p ≤.05), and depressive symptoms (AUC = .63, p ≤.05). The following items were not statistically significant (p >.05): cognitive impulsivity, poor planning, motor impulsivity, cognitive anger, arousal, angry behaviour, and regulatory ability. Physical aggression towards staff was predicted by angry behaviour (AUC = .68, p ≤.05), but no other items. Physical aggression towards patients was predicted by positive psychotic symptoms (AUC = .65, p ≤.05), hostility (AUC = .69, p ≤.01), and depressive symptoms (AUC = .68, p ≤.01), but no other items.
Mckenzie & Curr (2005)	Physically aggressive incidents: 70	Physical aggression was predicted by negative attitudes (AUC = .66, p = .019) and impulsivity (*AUC = .77, p <.001). Lack of insight, active symptoms of mental illness, and being unresponsive to treatment were not statistically significant (ps >.05).*
Meaden et al. (2013)	Physically aggressive incidents: 9	Twenty-three risk factors were identified by staff as early warning signs of physical aggression for 24 patients: Contextual factors: contact with family (n = 4).

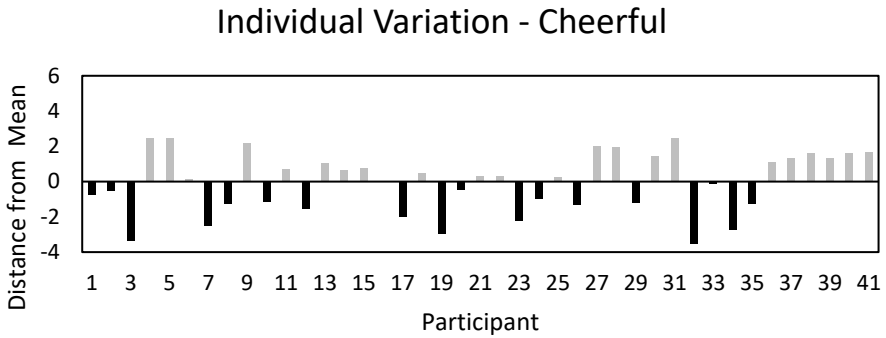
		Verbal factors: erratic speech (*n* = 7), increased pre-occupation with delusions (*n* = 7), increased conviction in delusions (*n* = 5), increased complaints about inpatients (*n* = 4). Behavioural factors: increase in demands (*n* = 14), increased bad language/swearing (*n* = 13), social withdrawal (*n* = 13), staring (*n* = 12), pacing (*n* =11), refusal to take medication (*n* = 9), vocalising out loud (*n* = 9), increased smoking (*n* = 8), invading personal space (*n* = 8), decrease in personal hygiene (*n* = 6), erratic sleep patterns (*n* = 6), refusal to eat (*n* = 6), increase in insults/threats (*n* = 5), quiet (*n* = 5), loss of engagement in activities (*n* = 4), refusal to take advice (*n* = 4), shouting or talking loudly (*n* = 10), and ignoring staff or losing engagement with them (*n* = 10).
		Identified risk factors were rated as significantly more relevant than dummy risk factors by nurses (t = 19.28, p <.01) and clinicians (t = 21.78, p <.01).
Ogloff & Daffern (2006)	Physically aggressive incidents: 111	Participants who were aggressive in a 24-hour period were more likely to be rated as irritable, impulsive, unwilling to follow directions, sensitive to perceived provocation, easily angered when requests denied, displaying negative attitudes, and verbally threatening, than those who were not aggressive (χ^2=11, p = <.001).
Reeves (2015)	Physically aggressive incidents: 13 Verbally aggressive incidents: 17 Property aggression incidents: 1	Verbal threats (φ = .175, p = .012), unwillingness to follow directions (φ = .182, p = .009), being easily angered when requests are denied (φ = .137, p = .048), negative attitudes (φ = .312, p = <.001), and hostility (φ = .173, p = .013) were significantly related to the occurrence of aggressive incidents. Confusion, irritability, boisterousness, physical threats, attacking objects, impulsivity, sensitivity to perceived provocation, intoxication, and suspiciousness were not statistically significant (ps >.05).
Selenius et al. (2016)	Physically/verbally aggressive incidents: 74	Participants who had self-harmed during inpatient care were significantly more likely to be verbally (χ^2=6.67, p = .010) and physically aggressive towards staff (χ^2=9.19, p = .002) than those who had not self-harmed. Self-harm was not significantly associated with verbal or physical aggression towards other patients (ps >.05).

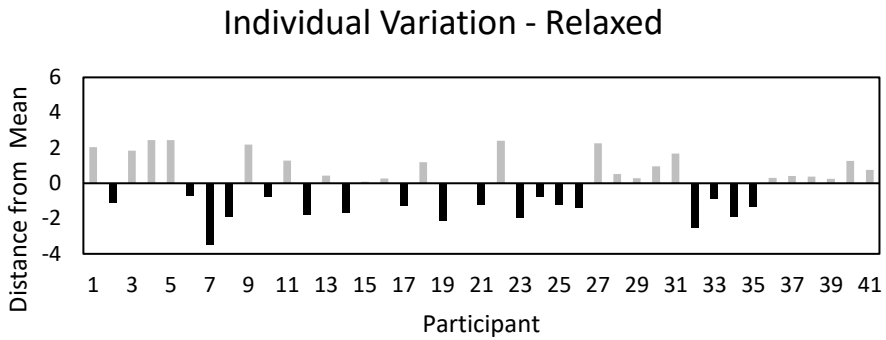
Schuringa et al. (2018)	Physically aggressive incidents: 53	There were significant differences in impulsivity (p <.001, d = -.82), antisocial behaviour (p <.001, d = -1.08), hostile behaviour (p <.001, d = -1.00), manipulative behaviour (p <.001, d = -.64), compliance to rules (p <.001, d = -.78), antisocial associates (p <.001, d = -.82), and drug use (p = .02, d = -.51) among those who were aggressive, compared to those who were not. Sexually deviant behaviour and psychotic symptoms were not statistically significant (ps >.05).
Steptoe et al. (2008)	Not reported	Physical aggression was predicted by mood/emotion (*AUC = .74, p <.001), antisocial behaviour* (*AUC = .70, p <.001), intolerance/agreeableness* (*AUC = .71, p <.001), violence self-regulation* (*AUC = .66, p <.01), and agreement with routine* (*AUC = .66, p <.01). Sexual self-regulation, substance use, and opportunity for victim access were not statistically significant (ps >.05).*
Tengström et al. (2006)	Physical aggression [b]: Schizophrenia: 7.07 (SD=11.46) Personality Disorder: 8.37 (SD=12.43) Cognitive Impairment: 19.27 (SD=23.36)	In the schizophrenia group, negative attitudes (r = .42, p <.01) and impulsivity (r = .39, p <.01) were significantly associated with aggressive incidents. Lack of insight, active symptoms of major mental illness, being unresponsive to treatment, plans lacking feasibility, exposure to destabilisers, lack of personal support, noncompliance with remediation attempts, and stress were not statistically significant (ps >.05). In the personality disorder group, lack of insight (r = .43, p <.01) and negative attitudes (r = .39, p <.01) were significantly associated with aggressive incidents. The remaining 8 items were not statistically significance (ps >.05). In the cognitive impairment group, impulsivity (r = .53, p <.01), negative attitudes (r = .42, p <.01), and noncompliance with remediation attempts (r = .44, p <.01) were significantly associated with aggressive incidents. The remaining 7 items were not statistically significance (ps >.05).
van de Sande et al. (2017)	Episodes of seclusion: 444	Seclusion was significantly associated with psychological functioning (Ex (b) = 1.91, p = .029), motivation (Ex (b) = 2.19, p = .004), anxiety (Ex (b) = 1.50, p = .012), emotional withdrawal (Ex (b) = 3.02, p = .011), tension (Ex (b) = 1.08, p = .014), suspiciousness (Ex (b) = 1.56, p <.001), blunted affect (Ex (b) = 2.41, p <.001), and bizarre behaviour (Ex (b) = 1.82, p <.001). Twenty-two items were not statistically significant (ps >.05): social skills, self-care, substance abuse, somatic concerns, conceptual disorganization, guilt, mannerisms and posturing, grandiosity, depressive mood, hostility, hallucinations, motor retardation, uncooperativeness, unusual thought content, excitement, disorientation, elevated mood, motor hyperactivity, distractibility, helplessness, self-neglect, and sexual preoccupation.

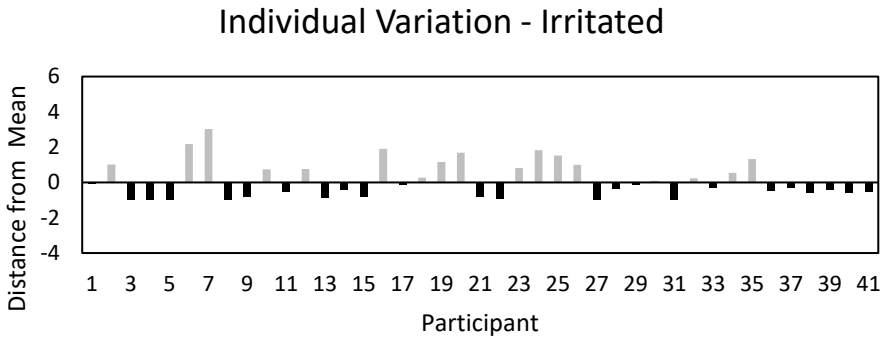
van de Sande et al. (2013)	Episodes of seclusion: 154	Seclusion was significantly associated with confusion (Ex (b) = 2.95, *p* <.001), psychological impairment (Ex (b) = 0.96, *p* <.001), and social functioning (Ex (b) = 0.96, *p* <.001). Six items were not statistically significant (*p*s >.05): irritability, boisterousness, physical threats, verbal threats, attacking objects, and self-care.
Wang & Diamond (1999)	Physical aggression: .16 (SD = .41)[c]	Structural equation modelling indicated strong relationships between anger and verbal (path coefficient = .84) and physical aggression (path coefficient = .67), and antisocial personality style and verbal (path coefficient = .26) and physical aggression (path coefficient = .37). Impulsivity was weakly related to verbal aggression (path coefficient = -.18), and not related to physical aggression.
Werner et al. (1983)	Physically aggressive incidents: 12	Physical aggression was significantly associated with emotional withdrawal (*r* = -.42, *p* <.001), hallucinatory behaviour (*r* = .37, *p* <.05), and psychomotor retardation (*r* = -.32, *p* <.32). Fifteen items were not statistically significant (*p*s >.05): somatic concern, anxiety, conceptual disorganization, guilt, tension, mannerisms and posturing, grandiosity, depressive mood, hostility, suspiciousness, uncooperativeness, unusual thought content, blunted affect, excitement, and disorientation.
Whittington et al. (2006)	Episodes of restrain: 261	Restraint was significantly associated with self-harm (OR = 6.69, *p* = .007), personal gain (OR = 0.21, *p* = .014), bad news (OR = 0.37, *p* = .045), unclear thoughts (OR = 2.31, *p* = .025), and increased volume (OR = 2.14, *p* = .033).
Whittington & Patterson (1996)	Physically aggressive incidents: 31	Twenty-six risk factor were reported by staff five minutes prior to a physical assault: verbal abuse, high overall activity, standing uncomfortably close, loud voice volume, glaring eye contact, swearing, threatening gestures, fast voice speed, threatening stance or posture, high voice pitch, verbal threats, aggressive to objects, avoiding eye contact, confused or disorientated, deluded, crying, low voice pitch, slow voice speed, hallucinations, quiet voice volume, low overall activity, variable pitch, variable volume, variable speed, variable activity level, variable eye contact. Compared to participants who were not aggressive, verbal abuse (*p* <.05), threatening gestures (*p* <.01), threatening stance (*p* <.01), and abnormal activity level (*p* <.05) were significantly more common among participants who were aggressive.
Woods et al. (2015)	Physically aggressive incidents: 39[d]	Aggression was predicted by irritability (AUC = .72, *p* <.001) and verbal threats (AUC = .61, *p* <.001). Confusion, boisterousness, physical threats, and attacking objects was not statistically significant (*p*s >.05).

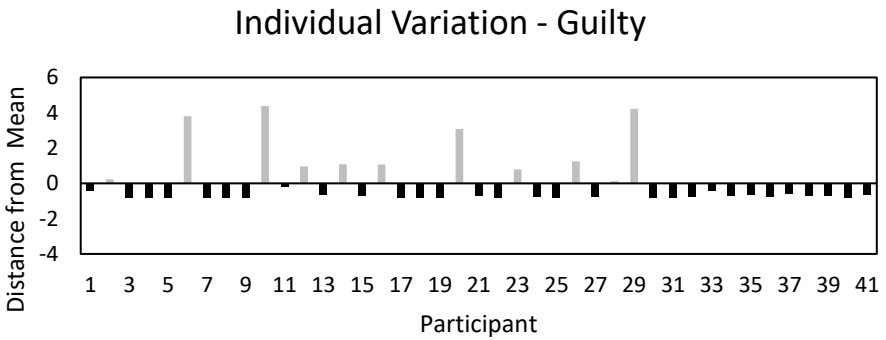
Verbally aggressive incidents: 42 [d]

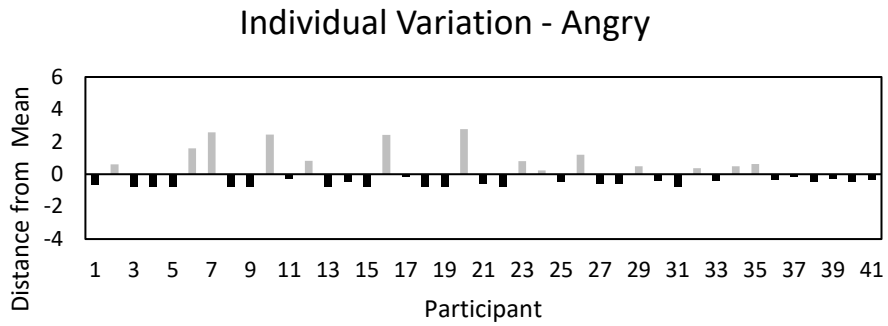
11.2 Appendix 2-Individual variation about the mean










Individual Variation - Angry
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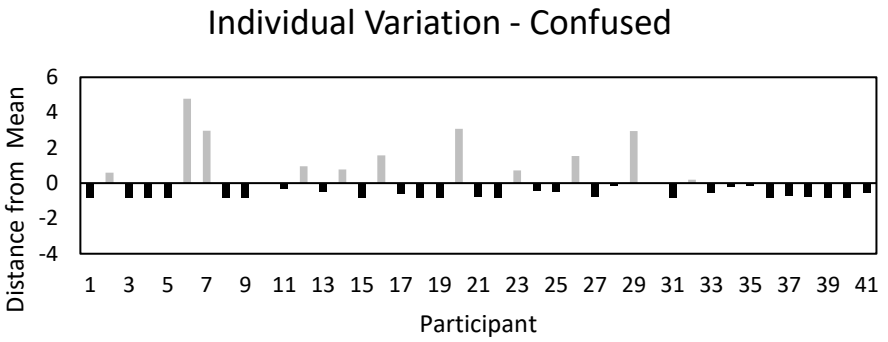
Participant


Individual Variation - Confused
Distance from Mean
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-4
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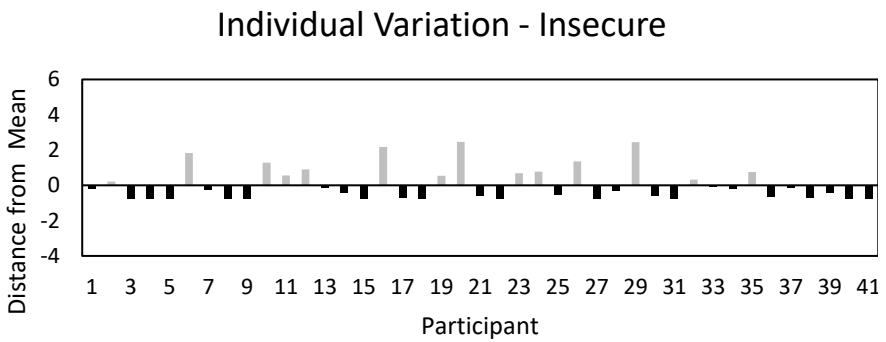
Participant


Individual Variation - Insecure
Distance from Mean
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-4
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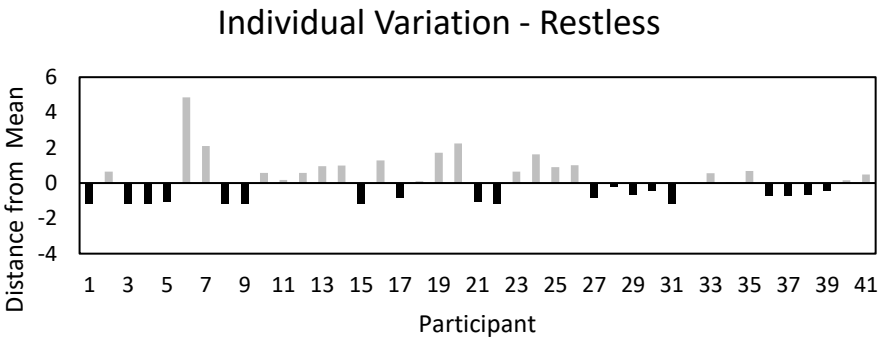
Participant


Individual Variation - Restless
Distance from Mean
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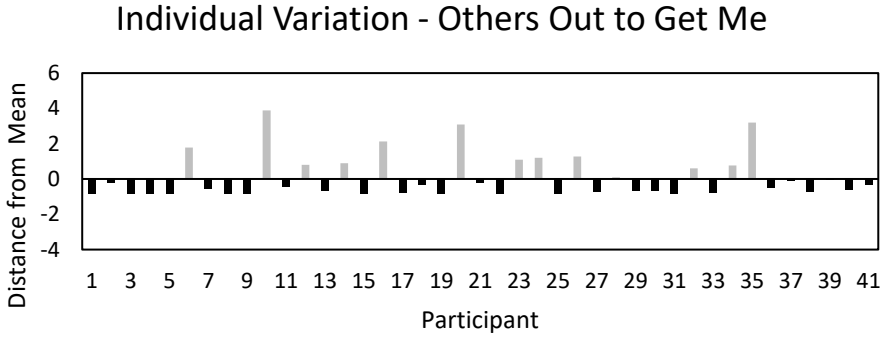
Participant


Individual Variation - Others Out to Get Me
Distance from Mean
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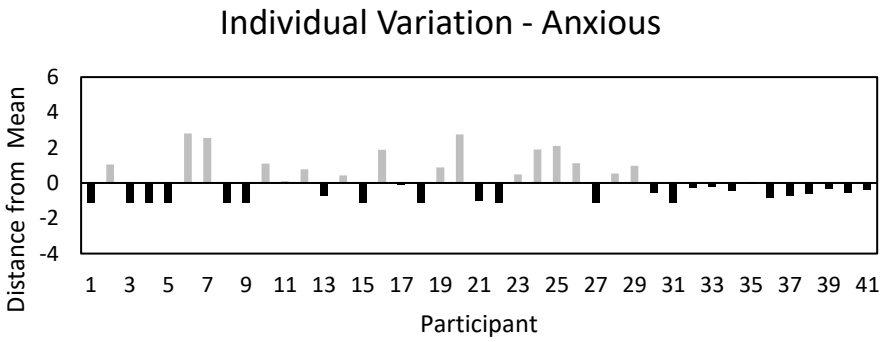
Participant


Individual Variation - Anxious
Distance from Mean
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-4
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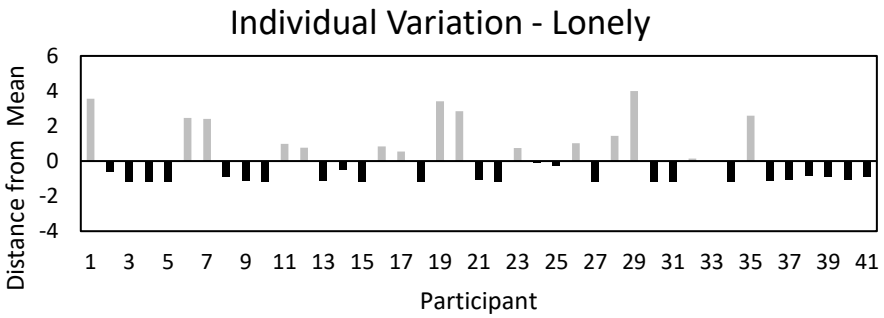
Participant


Individual Variation - Lonely
Distance from Mean
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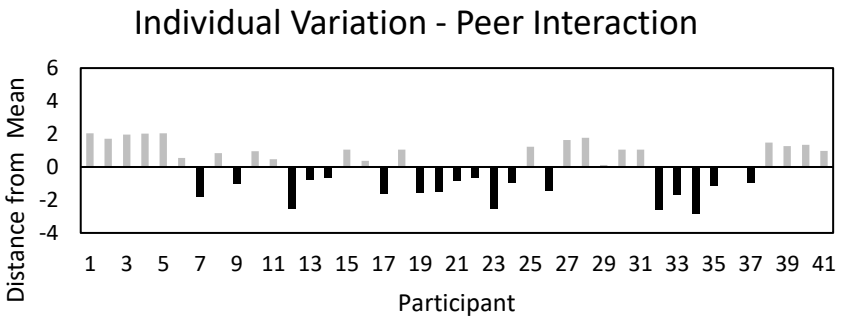
Participant


Individual Variation - Peer Interaction
Distance from Mean
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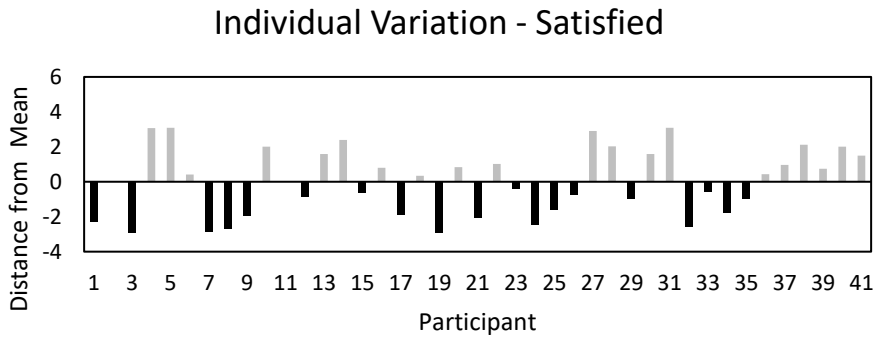
Participant


Individual Variation - Satisfied
Distance from Mean
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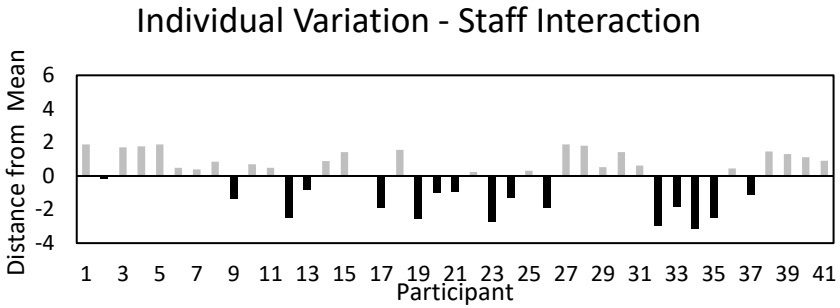
Participant


Individual Variation - Staff Interaction
Distance from Mean
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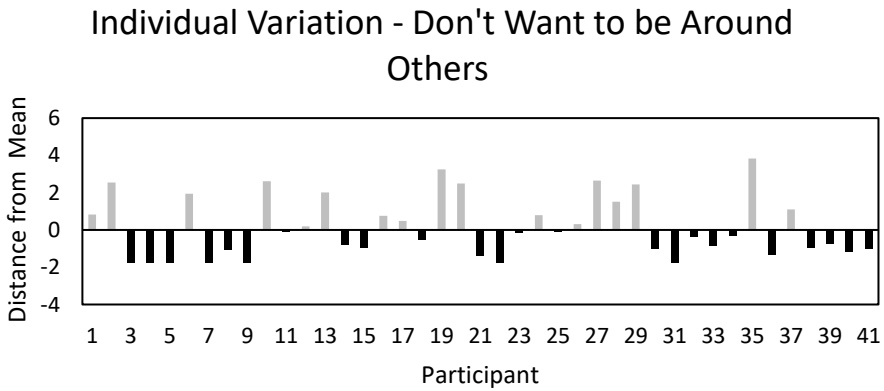
Participant


Individual Variation - Don't Want to be Around Others
Distance from Mean
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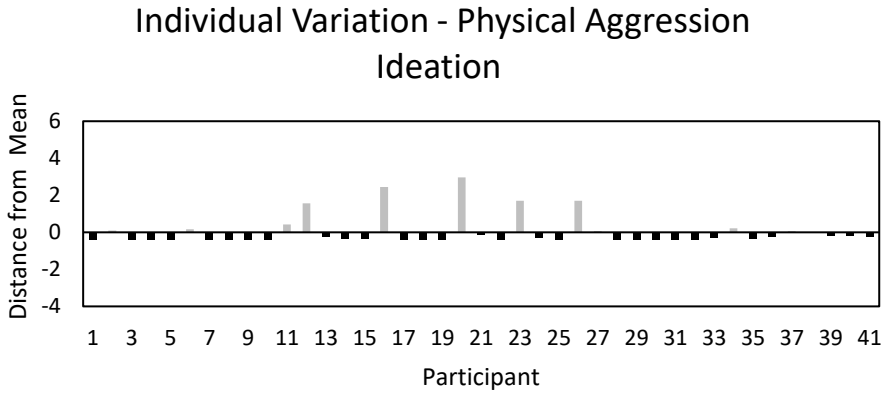
Participant


Individual Variation - Physical Aggression Ideation
Distance from Mean
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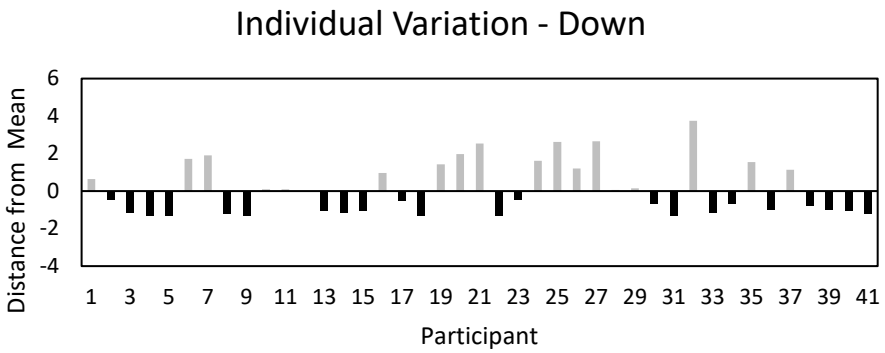
Participant


Individual Variation - Down
Distance from Mean
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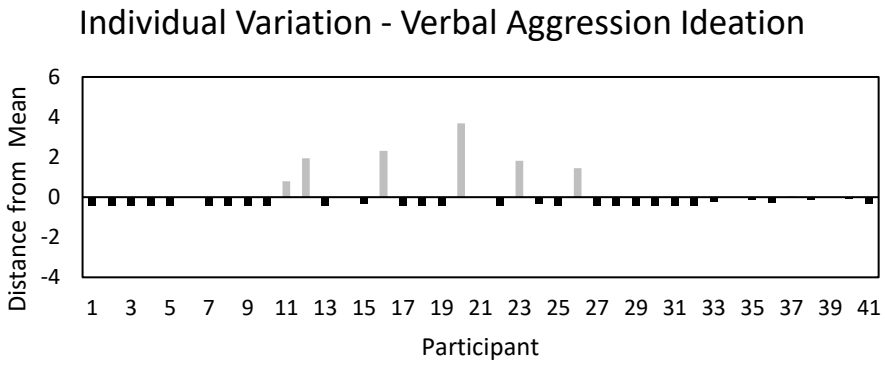
Participant


Individual Variation - Verbal Aggression Ideation
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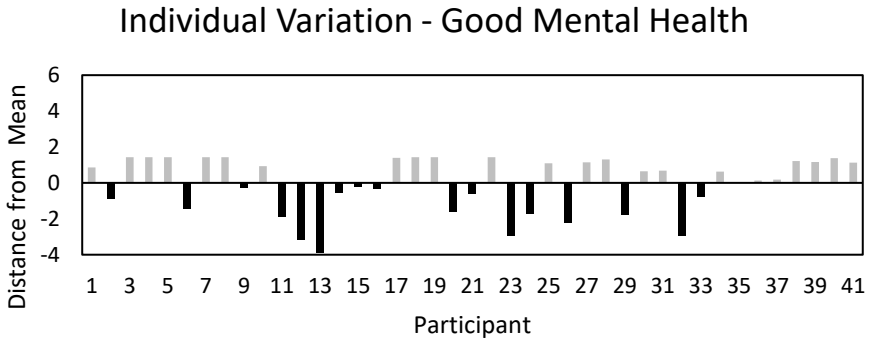
Participant


Individual Variation - Good Mental Health
Distance from Mean
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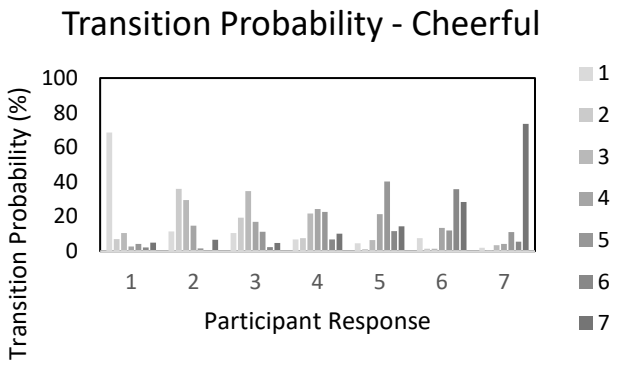
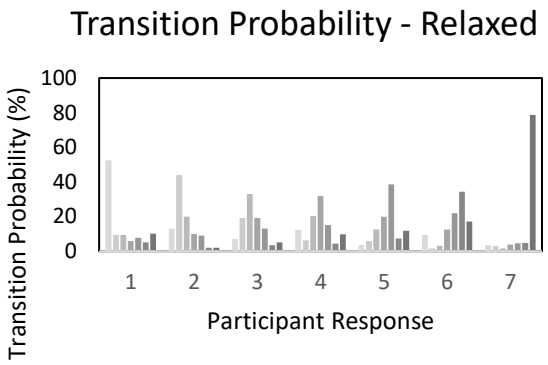
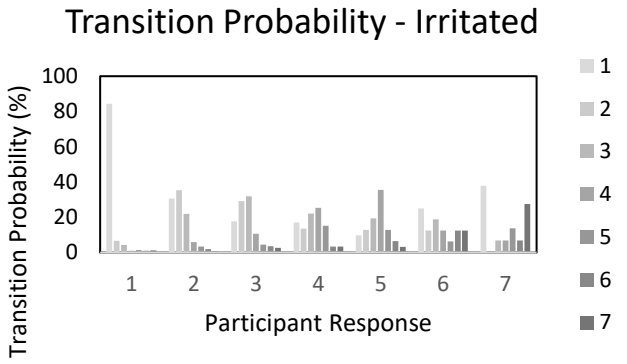
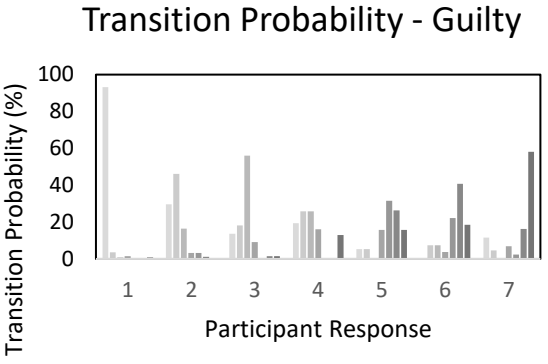
Participant

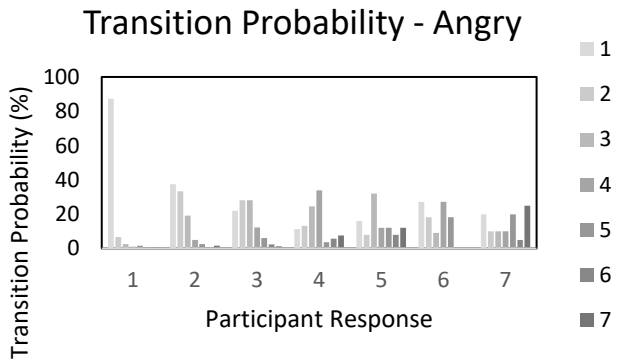
11.3 Appendix 3-Transition probabilities.

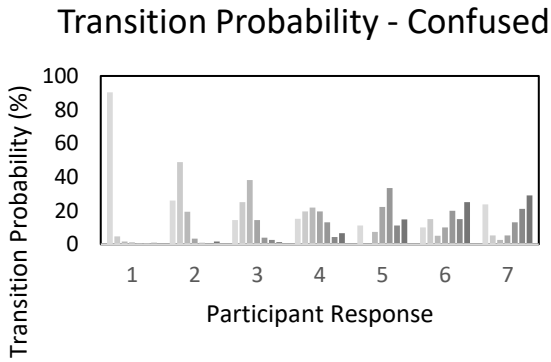


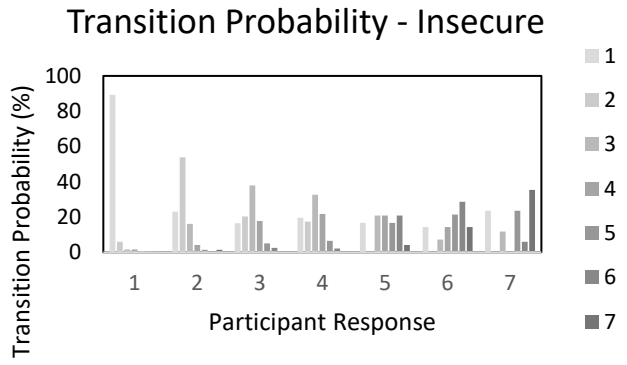


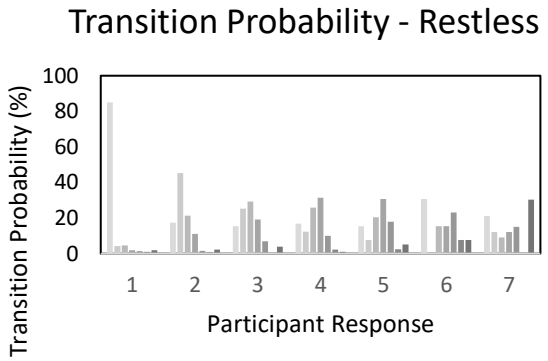


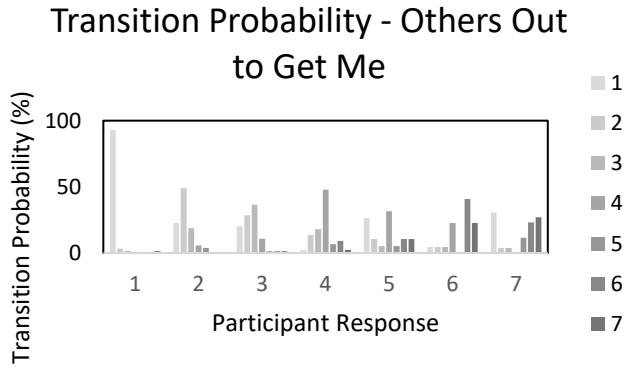


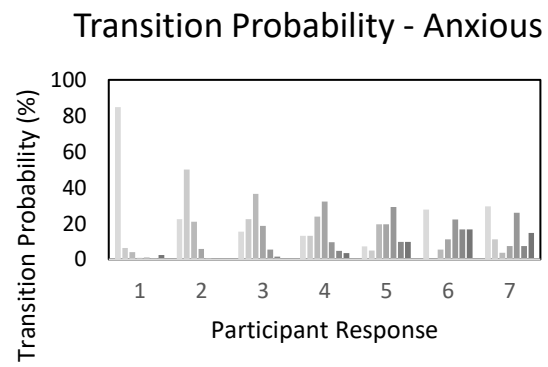


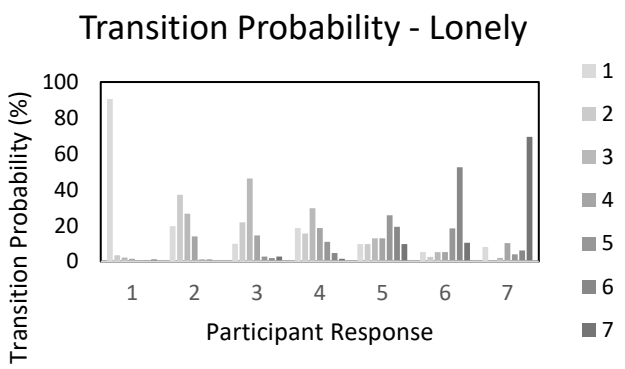


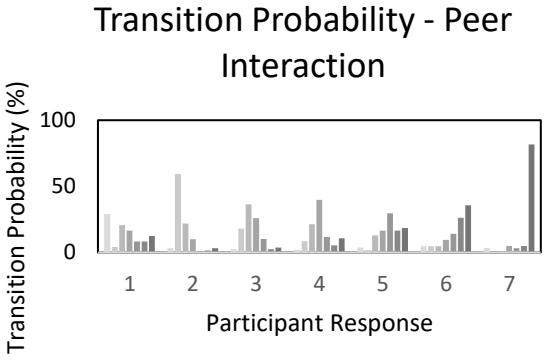


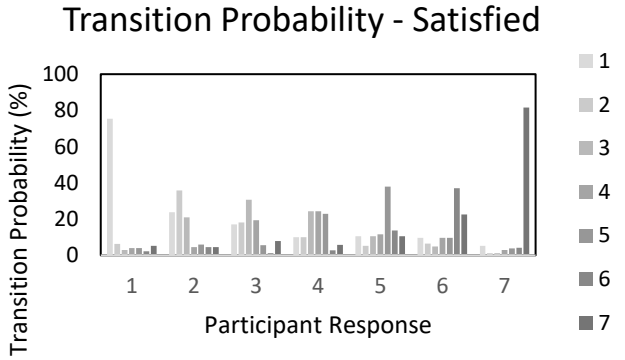


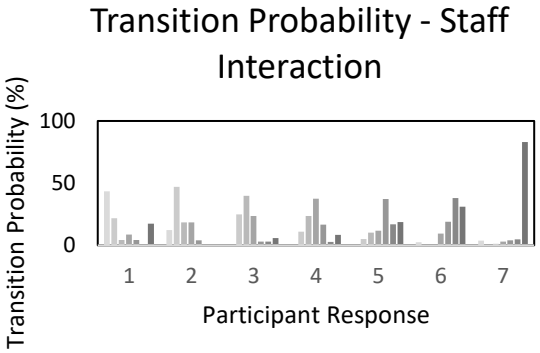


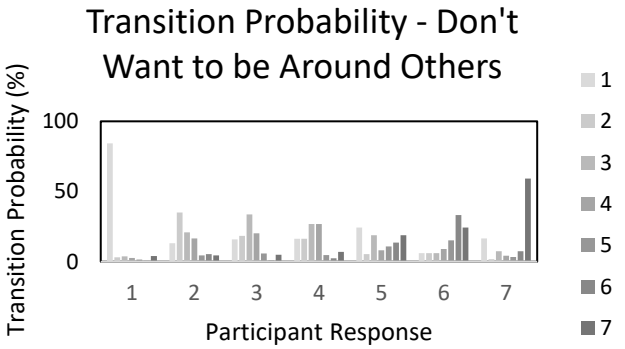


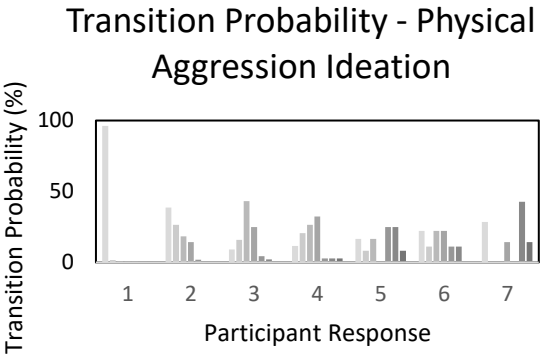

Transition Probability - Lonely
Transition Probability (%)
100
80
60
40
20
0
1 2 3 4 5 6 7
Participant Response
1
2
3
4
5
6
7

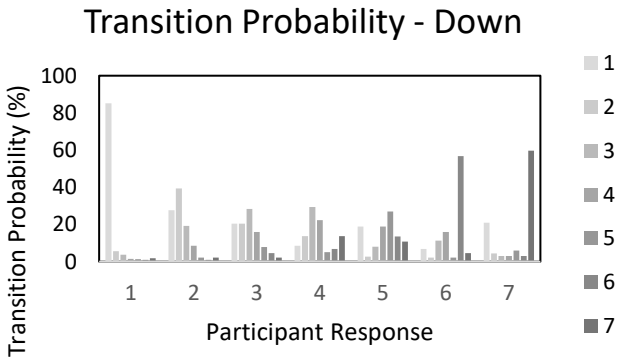

Transition Probability - Peer Interaction
Transition Probability (%)
100
50
0
1 2 3 4 5 6 7
Participant Response

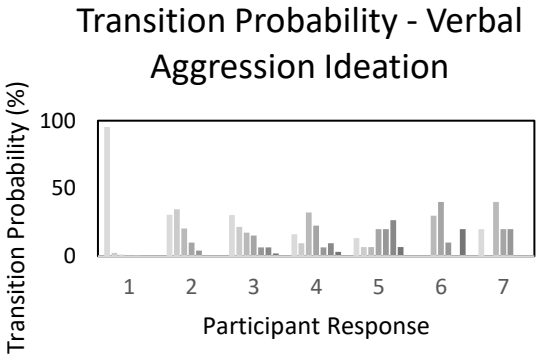

Transition Probability - Satisfied
Transition Probability (%)
100
80
60
40
20
0
1 2 3 4 5 6 7
Participant Response
1
2
3
4
5
6
7

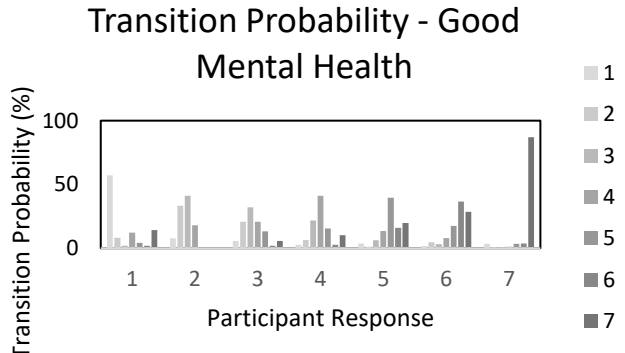

Transition Probability - Staff Interaction
Transition Probability (%)
100
50
0
1 2 3 4 5 6 7
Participant Response


Transition Probability - Don't Want to be Around Others
Transition Probability (%)
100
50
0
1 2 3 4 5 6 7
Participant Response
1
2
3
4
5
6
7


Transition Probability - Physical Aggression Ideation
Transition Probability (%)
100
50
0
1 2 3 4 5 6 7
Participant Response


Transition Probability - Down
Transition Probability (%)
100
80
60
40
20
0
1 2 3 4 5 6 7
Participant Response
1
2
3
4
5
6
7


Transition Probability - Verbal Aggression Ideation
Transition Probability (%)
100
50
0
1 2 3 4 5 6 7
Participant Response


Transition Probability - Good Mental Health
Transition Probability (%)
100
50
0
1 2 3 4 5 6 7
Participant Response
1
2
3
4
5
6
7

11.4 Appendix 4 - Guidelines for reporting articles on psychiatry and heart rate variability (GRAPH) checklist items.

Topic	Item number	Checklist item	Reported on page number
Selection of participants			
Clinical group recruitment and selection	1a	Psychiatric group recruitment details and illness assessment methods.	111
Control group recruitment and selection	1b	Control group recruitment details and methods to rule out psychiatric illness.	N/A
Inclusion criteria	1c	Description of inclusion criteria (e.g., absence of physical health conditions).	111
Disease characteristics	1d	Description of disease duration, severity, psychiatric comorbidities, and medication status.	111
Demographics	1e	Details on age, gender distribution, physical activity level, alcohol intake, and nicotine intake.	115
IBI collection			
Hardware/software details	2a	Brand, electrode configuration (if applicable)	85
IBI collection details	2b	Raw sampling rate, length of data collection, time of day, filtering, participant posture, and instructions.	85
IBI analysis and cleaning			
IBI calculation	3a	IBI calculation and resampling methods.	97
IBI artefact identification	3b	IBI artefact identification method (e.g., algorithm, manual inspection).	97
IBI data loss	3c	Reasons for loss (e.g., persistent ectopy, equipment failure)	97
IBI cleaning	3d	Artefact cleaning methods and the percentage of beats were corrected.	98
HRV calculation			
Method of analysis used	4a	Metrics used and the software/script used for HRV calculation, log transformation (if applicable)	98
Frequency bands used	4b	Specification of bands and how they were interpreted.	98

11.5 Appendix 5 - Publication recommendations for electrodermal measurements.

Item	Item number	Description	Reported on page number
Method of measurement			
Endosomatic/exosomatic	1a	Endosomatic or exosomatic recording.	85
Direct/Alternating current	1b	Direct or alternating current applied to the skin.	85
Constant voltage/current	1c	Constant voltage or constant current.	85
Applied voltage	1d	Applied voltage (or current).	85
Manufacturer details	1e	Manufacturer and instrument type (if commercially available instruments have been used).	85
Calibration procedures	1f	Calibration procedures conducted.	85
Signal conditioning			
EDL and EDR separation	2a	Procedures for separating ELD from EDRs.	N/A
Amplifiers	2b	Time constraints of amplifiers (if applicable).	N/A
Grounding	2c	Grounding procedures used (if applicable).	N/A
A/D conversion	2d	A/D conversion rate.	N/A
Sampling frequency	2e	Sampling frequency.	4
Recording Sites			
Active/inactive electrodes	3a	Recording sites for active and inactive electrodes (if applicable).	N/A
Pre-treatment	3b	Pre-treatment procedures for the recording site (if applicable).	N/A
Electrode details	3c	Description of electrodes (i.e. metal, area of contact, method of fixation, brand and type).	85
Electrolyte details	3d	Description of electrolytes used (i.e. gel or base, ionic type and concentration).	85
Electrode attachment	3e	How long the electrodes were attached before the recording started and stayed in place.	N/A
Polarization	3f	Details of how polarization were controlled and how electrodes were stored.	N/A
Signal evaluation			
Time windows	4a	Description of the time windows for tonic and phasic measures.	97
Minimum amplitude	4b	Description of the minimum amplitude criteria for EDRs.	97

Artefacts	4c	Description of methods of detection and elimination of recording artefacts.	98
Baseline conditions	4d	Details of baseline condition (i.e. length and statistical treatments during data analysis).	N/A
Participant Details			
Demographics	5a	Details on gender, age, and ethnicity. Details on medication or drug use.	115
Environmental factors	5b	Details on inside and outside temperatures and relative humidity.	N/A