Exploring personalised virtual reality experiences using real-time user-tracking data in application to loneliness interventions

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Declaration

This work has not been previously accepted in substance for any degree and is not being concurrently submitted in candidature for any degree.

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Abstract

Intervention strategies employed in the treatment of chronic loneliness are commonly found to be ineffective, which has particularly been attributed to their lack of focus on detrimental intrinsic cognition, disregard for the diverse structure of loneliness, and the minimal personalisation of treatment regarding individuals' needs and contexts. Loneliness is a significant health concern with its causal influence on psychological functioning, cognitive decline, heart-related illnesses, and especially in the older population, morbidity and premature mortality. Given this importance, effective treatment strategies are vital in managing such wellbeing implications.

Extensive research in various mental health technologies highlights the innovative application of user-tracking sensor data in the analysis of individual conditions, as well as immersive virtual reality devices that are beneficial within cognitive behavioural therapy intervention strategies. Both technologies are consistently found to be successful across a wide range of healthcare domains, however recent work has explored the combination of such applications, which have high potential in the personalised and multidimensional treatment of loneliness, consequently addressing the negative internal functioning that limits psychological progression.

To investigate this potential, the methods applied in these technology applications are reviewed and compared in relation to loneliness and current intervention limitations, identifying the concepts most successful in related work. Utilising this analysis, a virtual reality application is developed in conjunction with real-time sensor data, analysing user behaviour in order to influence the virtual experience. As such, cognitive behavioural therapy approaches are incorporated, aiming to encourage behaviours that are successful in addressing hypervigilance, said to be one of the most harmful symptoms of loneliness. Through the human-centred development employed, mitigation of each concern

regarding traditional loneliness treatment is incorporated into the design, intending to demonstrate the suitability and effectiveness of such technology within a loneliness context.

Preliminary evaluation of the developed system is achieved through user studies, in which results identify the successful application of such technology through participant beliefs and experiences regarding perceived purpose, appropriateness of functionality, and incorporation of literature concepts. In comparison with the overarching literature, these results conclude the suitability of combining real-time sensor data and virtual reality technology in application to loneliness treatment.

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Contents

Chapter 1

Introduction

Mental health and wellbeing have gained increasing awareness over recent years, with escalating rates of common mental disorder diagnoses such as depression, anxiety and OCD, among many others [1, 2]. In January 2020, 1 in 6 adults were estimated to have a common mental disorder in England [3], with parliament's 2020 mental health statistics report stating plans to spend £13 billion on mental health, learning disabilities and dementia services, forming 14.1% of local NHS funding allocations [3, 4].

The significance of mental health further intensified with the Covid-19 pandemic, particularly through its restrictions and lockdown measures [1, 2, 5]. Studies published in May 2021 found that approximately 52% of a UK-representative population sample screened positive for a common mental disorder, with consistent indications of more severe mental illnesses in various subcategories of participants such as young adults, women, the unemployed, and those with low household incomes [5]. Depression, anxiety and insomnia in particular were found to be much more prevalent in comparison to pre-pandemic conditions, and the effects of the pandemic on the UK population's mental health and general wellbeing are said to be severe and long lasting [2, 5].

In response to this impact, research and investments in technology solutions have been undertaken in an effort to make diagnosis and treatment more effective, efficient and accessible [6, 7]. Such innovations are currently trending towards smartphone applications for self-management and skill training, as well as devices for passive symptom tracking and data collection, forwarded to clinicians and researchers to both monitor patients' progress and improve the understanding of individuals and their conditions [6].

As such, a crucial field within mental health research is the analysis of data from user-tracking sensors, in which various types of sensing technologies are used in the identification and management of mental health symptoms, widely found to be successful in their accuracy and personalisation of treatment. For example, biomedical sensors such as heart rate monitors and galvanic skin conductors are valuable in the detection of anxiety attacks and PTSD episodes [8–10], whereas inertial movement sensors, typically accelerometers or gyroscopes, have been proven in their ability to analyse behaviours relating to stress [10, 11]. Sensor monitoring strategies are becoming increasingly more common within healthcare literature, especially with advances in machine learning and data processing techniques that can analyse large volumes of data for condition evaluation, progress tracking and future prediction [7, 10, 12–14]. Particularly, the diverse range of sensors embedded within everyday smartphone devices are often utilised for their ubiquity, not only improving access to treatment, but also improving the quality of gathered sensor data through more frequent and consistent use [8, 10, 15–18].

Although less common in practice, more modern technology innovations are also being explored in their application to mental health interventions, and a rapidly advancing and promising domain of such research is that pursuing virtual reality. Virtual reality offers the unique capability of immersing users within any defined environment without leaving the room [19, 20], and has been found to induce a realistic sense of presence inside the portrayed virtual world [20–25]. Within healthcare, these solutions are predominantly used for methods of exposure therapy [8, 19, 21, 26, 27] and distraction-based pain relief [28–31], and have especially demonstrated a high capacity in their cognitive behavioural therapy properties [19, 32–39]. In this sense, an enhanced state of presence within a virtual scenario or environment, tailored to the needs of an individual or particular mental health condition, produces much more naturalistic responses from patients than in laboratory situations [20, 40, 41], without the need for a specific external setup. Through guided support and virtual interactions, clinicians are able to understand and deal with patients' psychological responses to virtual stimuli, eventually encouraging a change in an individual's intrinsic negative behaviours through prolonged operation and experience

[19, 20, 38, 39, 42–44].

Various technology solutions have proven beneficial in diverse mental health contexts, and while the standard of these interventions continues to advance, loneliness is a particular condition that has not yet seen much utilisation of the advantages brought by technology innovations. Loneliness is most commonly defined as a distressing feeling that occurs when one's social needs are not met by the quality of existing relationships [14, 45–54], typically characterised by negative emotions such as desperation and self-deprecation as well as passive, self-absorbed and generally ineffective social behaviour [14, 55–59]. Correlating conditions like depression and anxiety may also contribute as both causal and resulting factors of loneliness [45, 50, 57, 60–62], which has often been associated with dementia and cognitive decline [14, 53, 63–67].

Many inadequacies have been highlighted in current loneliness interventions, and a review of both existing and upcoming technology innovations display great potential in addressing these limitations. Virtual reality in particular has been explored in improving the standard of treatment within various related mental health interventions, and recently, researchers have started to combine such technology with the use of sensor devices in order to create immersive experiences that adapt to user reactions within a virtual environment, analysing behavioural data emerging from physical, biological and psychological responses to perceived stimuli [20, 32, 36, 37, 68, 69]. Considering the prospective value of these solutions in a mental health context – and particularly in application to loneliness – there is hopeful potential in the progression and improvement of traditional measures regarding their current criticisms.

As a result, the proposed project involves extensive exploration of the suitability and potential regarding virtual reality and sensor technology when applied to a mental health context, specifically targeting loneliness symptoms through the development of a responsive cognitive behavioural therapy environment within virtual reality, accordingly personalising the interactive experience through real-time behavioural analysis of users' sensor data. User studies employing the developed application aim to evaluate the implementation of research in relation to loneliness concepts, and by comparing such findings with those discovered across the literature, a conclusion will be reached regarding the suitability of sensor-adaptive virtual reality innovations within loneliness or general mental health interventions, as well as their ability to improve upon the shortcomings of current, more traditional approaches applied to loneliness treatment.

Overall, this project intends to demonstrate more personalised, multidimensional and inherent psychological treatment than other methods tend to achieve, proposed as an introductory proof of concept that may either be expanded on in future iterations, or used as inspiration for more widespread research within the fields of loneliness and effective intervention strategies.

1.1 Loneliness and project motivations

The fundamental definition of loneliness widely agreed on in psychology literature denotes the distress that occurs with a perceived discrepancy between desired and existing social relationships, where a person's social needs are not met, predominantly by the quality rather than quantity, of these relationships [14, 45–54]. In this sense, loneliness concerns subjective social isolation in which a person may feel marginalised, excluded or misunderstood within relationships [50, 70], subsequently increasing vigilance for threat and heightening feelings of vulnerability [45, 71]. Generally, loneliness does not correlate with objective social isolation – namely, a lack of company – given that it may not necessarily cause such unpleasant experiences, and is in some cases enjoyable or even desirable [14, 45, 72].

Failing to satisfy the fundamental human need to socially belong can cause severe mental health and wellbeing disturbances, and therefore much of the literature surrounding loneliness and perceived social isolation argues that alleviating such distress should be a focus for clinicians [45, 55, 72]. While this importance has been highlighted throughout psychology research, academics widely argue that the condition is rarely given consideration, and is often overshadowed by more recognised mental health conditions like depression [45, 55, 56]. However, loneliness in itself has been found to have adverse consequences for one's cognition, emotional state, behaviour, and physical health [14, 45, 53, 56, 73, 74]. Large-scale studies on the condition of loneliness determine that nearly 20% of the US population suffer with loneliness as a severe chronic state [45, 53, 55, 75], which extends as high as 38% within some demographics, such as older females [76].

Loneliness has been identified as both a predecessor and cause for depression, anxiety and high stress levels [45, 50, 57, 60–62], as well as behavioural disorders such as drug or alcohol addiction [57]. In extreme cases, loneliness is also a contributing factor for suicide [50]. Implicit hypervigilance caused by loneliness further alters psychological processes that influence physiological functioning [45, 53, 63], reduce sleep quality [45], and particularly among the older population, increase morbidity and trigger premature mortality through weakening of the immune system [14, 45, 53, 56, 57, 60, 73, 77–79]. As a result, people who suffer from extreme loneliness are at an increased risk of various medical issues including strokes, cardiovascular disease, and other heart-related illnesses [14, 50, 53, 57, 60, 73, 77, 78]. One study even estimated that loneliness increases the likelihood of death by around 26% [79].

In particular, loneliness is often strongly associated with dementia and cognitive decline [14, 53, 63–66]. As well as being a modifying risk factor, data from the Amsterdam Study of the Elderly demonstrates that the early onset of dementia can be predicted by loneliness [67].

Despite the importance of mitigating such issues, researchers note the inadequacies of existing loneliness innovations, as well as failures in finding solutions that support loneliness at a widespread level [45, 53, 55–57, 80–85]. Regarding treatment, current strategies include social events aiming to develop connections with others, physical activities such as yoga classes and walking groups, and psychological treatment typically delivered through conversation-based cognitive behavioural therapy [45, 57, 86]. Not only have these interventions been deemed inaccessible, reaching less than half of the population suffering from loneliness due to factors like social stigma, lack of resources, skill gaps and misdiagnosis [57], but the majority of studies also find them largely ineffective [45, 53, 57, 80–83].

The unsuccessful nature of current interventions has been attributed to (1) their typical focus on objective social isolation, (2) disregard for the diverse structure of loneliness, and (3) the lack of approaches targeted at individuals' needs and contexts [45, 53]. Firstly, while group activities provide more social opportunities, they do not address the cognitive biases that characterise those suffering with loneliness [45] – various studies find that interventions targeting social interaction, social support and social skills are much less effective than those that address maladaptive social cognition, such as through cognitive behavioural training [45, 50, 53, 87]. In this sense, interventions directed at improving one's thoughts, behaviours and emotions – for example, changing the ways in which individuals consider and approach social relationships, identifying subconscious negative thoughts or biased cognitions, and reframing perceptions of self-control – are encouraged by loneliness experts, said to combat loneliness as well as social and emotional development at a more permanent level [45, 50, 53, 55]. However, a significant lack of such intervention strategies is continuously brought up in literature of this domain, despite the fact that maladaptive social cognition is a main factor in what makes loneliness such a large health risk [45].

Secondly, loneliness has been defined as a multidimensional condition that consists of various cognitive, emotional and behavioural variables [50, 53, 55, 88]. Additional research regarding these variables is essential in order to determine the causal relationships between loneliness and its characteristic features, and through a better understanding of any inherent correlations, the identification, assessment and treatment of subjective isolation can become more effective in its purpose [50, 55]. Current interventions rarely account for the diverse nature of loneliness and its related variables, diminishing their therapeutic quality and impact [45, 53, 56].

Similarly, some sources criticise current interventions for their minimal effort in personalising treatment [53, 55, 56], and stress that the experience of loneliness is vastly divergent between individuals, particularly across different circumstances and backgrounds [14, 45, 53, 56, 73]. A 'precision health' approach is explicitly called for, conveying that, although existing definitions of loneliness may represent the condition at its core, a one-size-fits-all solution is insufficient in effectively treating loneliness [53, 56]. Accordingly, the identification of prognostic digital biomarkers through machine learning techniques is a method that is starting to materialise through newfound motivations and requirements to find unique solutions tailored to individuals' needs [53].

In this sense, the project's main contribution is the experimental application of novel technology solutions that focus loneliness interventions towards subjective social isolation – namely, addressing maladaptive social cognition through methods of cognitive behavioural therapy – as well as adaptive treatment with the potential to accommodate individuals' needs and contexts, taking into account the diverse structure of loneliness and its multidimensional variables. Given that innovations surrounding physiological, biological, ambient and communication types of sensors have been successful in various aspects of healthcare and well-being, alongside therapeutic virtual reality solutions that can immerse users within any defined environment, combining the two technologies has vast potential in the area of loneliness, and is a possible solution in managing the shortcomings identified within existing interventions.

Consequently, the primary motivation is to encourage and inspire better intervention development for loneliness and its related mental health and wellbeing concerns, highlighting potential solutions and demonstrating the suitability of personal sensing alongside virtual reality environments in dealing with subjective isolation. Most crucially, such demonstration of this technology's suitability, as well as future work that builds on the current template developed, may eventually be directly beneficial in alleviating distress caused by loneliness for those suffering with the condition, therefore improving the standard of care which, while contributing to general health and well-being, can also assist towards the economic costs of healthcare, particularly regarding the high costs devoted to dementia and morbidity rates in general [53, 63, 89]. Further motives, subsequential to those previously mentioned, include the potential to improve the efficiency and knowledge of clinicians or loneliness experts in the field, particularly in terms of prevention, detection, management and treatment.

1.2 Project aims

In response to the motivations discussed, the following aims explicitly denote the objectives that will be carried out throughout the project, and are proposed as a means of evaluation regarding its success. Generally, work relating to each of these aims is covered in the background research, implementation and user study sections respectively, however they are also discussed collectively in the discussion and conclusion.

AIM 1: ***Explore the potential of personal sensing and virtual reality, separately and combined, both in their suitability for loneliness interventions and in their ability to improve upon the weaknesses of traditional loneliness interventions.***

As found within the field of loneliness, researchers commonly express that interventions addressing the internal psychology of patients, such as cognitive behavioural therapy, are more successful than those targeting social interaction [45, 50, 53, 55, 87]. In addition to this, current interventions are found to lack personalisation, instead employing a 'one-size-fits-all' approach [53, 55, 56] that does not consider loneliness as a complex and multidimensional condition [50, 53, 55, 56, 88].

Given that virtual reality and hardware sensors appear to be successful in many applications of, respectively, cognitive behavioural training and the identification and management of mental health conditions at an individual level, each of these technologies has potential in improving the weaknesses found in traditional loneliness interventions. A review of current innovations in application to mental health establishes that virtual reality provides a sense of immersion and presence in a virtual scenario in order to overcome psychological barriers within a controlled environment [20–25], whereas sensor data may be utilised to track individual user behaviours during daily routines and subsequently identify symptoms of various psychological disorders, typically through the training and application of machine learning models [7, 8, 10, 12–14].

Recently, researchers have investigated the concept of combining these technologies, allowing virtual environments to adapt and be influenced by user reactions [20, 32, 36, 37, 68, 69] which, in a healthcare context, may allow treatment to become more personalised with regard to individuals' responses and emotions, therefore augmenting such forms of cognitive behavioural therapy to elicit the most appropriate response based on collected behavioural data. Given these possibilities, exploring this potential through reviews on current literature, related work and state-of-the-art within these domains is essential in order to attain a foundational understanding of the research area, and the resulting suitability of such technologies for loneliness interventions.

AIM 2: ***Develop a prototype virtual reality application influenced by real-time sensor data, which represents a surface-level concept of such applications in relation to cognitive behavioural therapy and aims to demonstrate the potential of personal sensing and virtual reality within loneliness interventions.***

An overview of state-of-the-art technology demonstrates that virtual reality enables a sense of immersion and presence within any defined environment [20–25], along with the ability to adapt to individual users and contexts through various interactions and virtual simulations [19, 20, 38, 39, 42–44]. While this functionality can elicit a variety of user reactions within a controlled setting, such advantages appear to be unnatural, difficult or impossible to achieve using alternative technologies or methods [20, 40, 41]. Additionally, the experience induced by virtual reality has potential in its further augmentation through the use of sensors, allowing the virtual environment to react to user responses and provide more personalised and multidimensional treatment as a result [8, 10, 15–18].

To fully exploit these capabilities and demonstrate the potential of virtual reality therapy that dynamically responds to user-sensed behaviour, an application representing these concepts will be designed and developed in abidance to loneliness literature, relating to and building upon related work that has been successful in respective healthcare domains. Rather than presenting a cure to loneliness, the application instead intends to demonstrate a surface-level proof of concept regarding the cognitive behavioural therapy capabilities of sensor data in virtual reality systems. In this sense, employing purposeful use of sensors and unique virtual reality functionality is vital in order to demonstrate the technology's maximum potential in supporting people suffering with loneliness, and in improving the current interventions such that relevant and successful methods of treatment are incorporated successfully.

AIM 3: ***Evaluate the application of personal sensing in combination with virtual reality, specifically regarding their purposeful and functional appropriateness and their ability to improve upon the weaknesses of traditional loneliness interventions.***

Studies utilising virtual reality, sensor data, or a combination of both technologies are typically successful within healthcare, mental health and wellbeing domains, and so it is important to identify whether the employed methods and concepts can be applied to loneliness in similar ways. To address these ideas, a primary user study performed with the developed application aims to gather results that may help to determine the system's potential in changing loneliness-related behaviour, particularly regarding its functional performance, perceived purpose and appropriateness of incorporated functionality through exploration of participant experiences and opinions when using the application, therefore evaluating the suitability of this technology within a loneliness intervention context. Given the proof-of-concept nature of the project, such subjective results are gathered in preference of those validifying the success of resulting loneliness treatment, with various limitations and ethical concerns regarding clinical use of the introductory application for genuine loneliness therapy.

In analysis of this suitability, conclusions found throughout the study will be compared and contrasted with results found in related mental health interventions, as well as that of the overarching literature, to determine whether the combination of sensors and virtual reality technology may be beneficial in practical application to loneliness treatment, such that it is both appropriate in its purpose and has the potential to valuably impact for those suffering with chronic loneliness.

1.3 Responsible research and innovation

This project aims to both utilise and maximise the potential of technology in supporting those who suffer with loneliness and resultant mental health issues, compliant with psychological findings and literature in how to best deal with such conditions. Prototype software and preliminary findings are built with a human-centred approach conforming to the principles of responsible innovation, which as a result, underpins the motivations and goals of the project. Given the exploratory nature of this research, ethical concerns are minimised through restricted application, and the project may be used as a means to encourage more informed loneliness interventions that address the concerns raised when using existing methods deemed less effective.

Chapter 2

Background research

Analysis of current literature and state-of-the-art research in virtual reality and sensor technology is important in order to gain a foundational understanding of such concepts, not only in their effectiveness in application to loneliness interventions, but also in identifying the key principles and methods that are successful across mental health innovations. As a result, the two technologies are first examined in isolation, targeting the healthcare applications of sensor data and virtual reality respectively, and are then explored in their synchronous combination. Through the evaluation of current advancements within these domains, their relevance and suitability regarding loneliness interventions, as well as their improvement of the traditional approaches commonly used, are discussed throughout.

2.1 Personal sensing

Over recent years, an emerging interest in ubiquitous sensing technology has become apparent in healthcare research communities, particularly in application to mental health. A subset of this domain, 'personal sensing', has been defined as the collection and analysis of data gathered from sensors embedded in the context of everyday life, aiming to identify human behaviours, thoughts, feelings and characteristics [10, 13, 90–94]. While some studies still regard personal sensing to be in its infancy, they also note the high potential of its applications both in terms of research, and as a clinical tool for the next generation of healthcare interventions [10, 13].

Devices such as smartphones, smart watches, fitness bands and external hardware tools all include a range of embedded sensors, in which contextual information about people and the environment can be interpreted through raw data as well as by combining data from multiple sensors [10, 13, 90–96]. While the data itself may not reveal a person's physical or mental state, personal sensing is often undertaken as a means of recognising the behaviour emerging from its underlying physiological readings [10, 93]. Common information drawn from everyday sensors include physical activity levels [90], location status [91], mood [92] and communication habits [93], which in state-of-the-art models, may be analysed or predicted through machine learning techniques [10, 90, 92, 95, 96]. Typically, multimodal sensor approaches produce better results compared to the use of single sensors [95, 96].

Utilising these readings, sensors may have the potential to improve current loneliness interventions. For example, one disadvantage regarding the traditional monitoring of various mental disorders is the reliance on self-reported ratings, which not only require consistent, conscious and willing feedback from patients [15], but are highly subjective and particularly prone to recall bias due to their retrospective nature [10, 15]. In this sense, personal sensing mitigates these issues through automatic and continuous monitoring of objective sensor data, without the intrusive need for user engagement [10, 11, 17]. Given the volume and complexity of such data, machine learning and various processing techniques can be applied in order to extract meaning at a higher quality than possible through traditional means [10, 11, 15, 17], and for conditions that require long-term monitoring – for example, the relapsing tendencies of bipolar disorder patients lead to longer transitions between psychological states than conditions like anxiety or stress, and thus require monitoring over a longer period of time [10] – data history also provides methods of longitudinal follow-ups and future prediction [8–10].

Additionally, typical monitoring systems do not consider personal variables and the variability within and between individuals [10, 11, 17, 45, 53], therefore limiting the capability to understand and change patient behaviour through personal representation [10, 11, 50, 55, 97]. Particularly regarding perception sensitivity – for instance, detecting changes in patients over time – repeated sampling of absolute behaviours such as those captured through sensors has been shown to outperform traditional monitoring reports in real-world settings [98]. Studies stress that the accuracy and performance of both interventions and monitoring systems is heavily dependent on individual characteristics and context, where such personalised information provides more specific just-in-time services that adapt to each user and their contextual situation [10, 97, 98]. Garcia-Ceja et al. suggest that robust solutions must also consider different types of sensors, providing the example that software analysis like social media usage is not suitable for those who use such platforms infrequently, and that relying solely on physiological sensors may bring inaccuracies through bodily changes caused by external factors such as diet and nutrition, medication intake, physical exercise and illness [10].

Various types of sensors exist, comprising of communication devices such as those accommodating WiFi and Bluetooth, inertial sensors like accelerometers and gyroscopes that measure speed, direction and motion, biological sensors to measure activity of the human body such as heart rate, or ambient sensors extracting external environment information, including temperature and air pressure. During studies, ambient sensors tend to be installed in the environment in a fixed position, external to users such that they require no contact or interaction, whereas wearable sensors are portable and typically worn subconsciously by users throughout their daily activities [10]. Software sensing, which processes data from software applications such as the duration of social media usage or content within text messages, may also be used to gain insights about user behaviours [10]. The majority of work regarding sensor applications in healthcare relates to association with and detection of mental health conditions, with a limited number of innovations targeting forecasting – namely, predicting some future state based on the current input data [99] – due to its challenging problem area in machine learning [10, 99].

Given this potential, it is vital to understand the current research standards and modern technology in the healthcare research field. As such, reviewing relevant applications that utilise these sensors will establish a foundational knowledge base, presenting insight into current state-of-the-art solutions and novel innovations that provide further inspiration and influence for development in this area.

2.1.1 Smartphone sensors

Among patients, there is a growing interest in using mobile applications to track mental health conditions on a daily basis [100]. The increasing capabilities of smartphone devices give them great potential in the monitoring, treatment and self-management of various mental health conditions, with powerful computational power and memory capacity as well as a diverse range of embedded sensors that provide rich data which, through collection and analysis, can be leveraged to study human behaviour [10, 15, 17, 101]. Using smartphone applications, the collection of such data to monitor a patient's state and progress may also be augmented through graphical user interfaces to support therapy, utilising natural and intuitive designs in order to maximise human-computer interaction and communication [15, 18]. Touch-enabled displays have also been proven useful to support enhanced gesture-based input and visualisations [18].

Consequently, the potential of smartphone-based mental health interventions has been explored and demonstrated in many studies across the research area. For several of these studies, the primary goal of using smartphone interventions is to reduce healthcare costs and expand the coverage of such services to larger populations [8, 10, 15, 16]. It is stated that, in developed countries, almost every citizen owns at least one mobile phone, facilitating access for up to 4.5 billion users worldwide [102]. In this sense, smartphones have the potential to make interventions more accessible for patients, and to improve the efficiency and interactivity of care.

The familiarity associated with smartphones also provides better comfort and interaction for patients. Given that a smartphone is a personal device and is typically carried with the patient at all times [8, 18], a mobile phone may act as a wearable sensor within the user's pocket, useful for automated data collection [10, 15], real-time feedback about behavioural patterns [8, 15], and for timely and directed education or advice [15]. The familiarity and subconsciousness of using a familiar device, as opposed to external sensors that may be attached to the body, minimises the observer effect during data collection [10, 11, 103, 104] and causes no additional discomfort for patients [15, 103, 104], which has further been shown to reduce the stress of monitored patients [105] and increase autonoetic consciousness through confluent use and self-awareness [9]. Results from many studies show significant improvements to adherence and compliance when participants use their own personal smartphone, particularly for mental health interventions as well as for monitoring conditions through self-reporting questionnaires [15, 106–109], especially compared to traditional self-assessment diaries written on paper [106].

2.1.1.1 Software sensing

For loneliness specifically, emerging technology applications appear to revolve around software-based sensing that analyses behaviour on a semantic level, typically using natural language processing techniques on social media usage or text message data [15, 57, 85, 110]. Existing studies involving these methods mainly focus on the collection of self-assessment data through analysis of text-based messages, sometimes as a means of feedback that can be analysed by professionals [15, 101].

In particular, Badal et al. aimed to challenge the current loneliness interventions limited by self-reporting approaches, instead employing natural language processing to systematically evaluate and quantify sentiment in addition to identifying features that may indicate or predict loneliness within both qualitative and quantitative assessments of text [85]. Using purely linguistic features, their trained machine learning models were able to predict qualitative loneliness with an accuracy of 94%, and quantitative loneliness with 76%. One interesting finding was that individuals suffering with loneliness typically gave longer responses with greater expression of sadness in response to direct questions about loneliness, and results also indicated that women are more likely to endorse feelings of loneliness within qualitative replies, while male responses included a combination of both "fearful" and "joyful" words.

Another study by Altschul et al. emphasised the importance of personality traits in loneliness interventions, deploying a smartphone application to passively detect a user's level of loneliness from communication and interaction patterns in phone-use behaviour through calls, text messages, browsing patterns and social media usage, while also taking personality into account [57]. Machine learning classifiers were used to detect loneliness through software sensing, which could categorise a user's range of loneliness with 98% accuracy, and through further analysis of the collected data, extraversion and emotional stability were two significant features found to inversely correlate with smartphone-sensed loneliness. These findings are consistent with prior work in personality-dependent loneliness, in which personality-dependent variables such as anxiety and neuroticism are stated to be positively associated with loneliness, while aspects like extraversion and self-esteem negatively contribute to loneliness [14, 55–59].

Outside of loneliness interventions, similar works utilise text message analysis to calculate ratings that denote the user's mood [110, 111], change patients' behaviour in terms of medical adherence and socialisation [112, 113], and to deduce statistical information from text-based logs, such as the length of messages and variations in length, or the number of messages sent and received every day [101, 114].

2.1.1.2 Acoustic sound

In healthcare research, smartphone applications have also been used to analyse external sensor data such as speech captured through its in-built microphone. Acoustic voice analysis in particular is said to be a well-explored field of research, and results from many studies prove its usefulness in both identification and classification of various mental health conditions [15, 115–122]. Given this potential, the analysis of phone calls is a common method of studying features and correlations through speech and voice – the three main techniques covered in the field include semantic analysis that focusses on the content of speech, acoustic analysis to extract aspects of the voice such as tone, pitch and flow, as well as activity analysis, which emphasises the assessment of a user's behavioural patterns regarding phone calls [15].

Several examples of successful voice recognition techniques exist throughout mental health and wellbeing research, particularly in the field of depression. Acoustic features such as pauses or the rate of one's speech have been known to correlate with depression, and are also established measures of identifying the condition during diagnosis [115, 116]. Additionally, strong connections between decreased communication abilities, frequency of social contact and resultant disorders like depression have been found [123–125], which provides further information to be used in automated intervention strategies [126]. Utilising such knowledge, AI voice recognition has been used to detect depressive episodes to a standard comparable with that of live interviews, with high accuracies demonstrated in multiple languages [126].

Crucially, Lu et al. identified physiological changes in the speech production process correlating with stress, and proposed an unobtrusive smartphone application to recognise stress levels using the in-built microphone through voice analysis alone [118]. Authors of this study claim that the application is the first of its kind in its ability to adapt underlying machine learning models in diverse acoustic environments, achieving 81% accuracy when indoors and 76% outdoors. These accuracy scores are improved through the utilisation of personalised models, achieving nearly 83% and 80% for indoor and outdoor environments respectively – however, this approach requires separate training for each individual user, limiting its scalability as well as usability in early stages of use. As a result, model adaptation is considered the most reliable method, initialising the application with a universal classification model and improving its capabilities through continuous access to more personal data.

Vocal production is widely acknowledged to be influenced by stress, and many studies utilise emotion detection as an associated factor [118–122, 127, 128]. In comparison to these studies, the main contribution provided by Lu et al. is the application's adaptability regarding external, unseen environments, with a classification pipeline that runs in real-time through off-the-shelf smartphone devices. Typically, voice recognition research is conducted on high-quality acoustic data with little background noise or background disruptions [118], however the achieved results demonstrate the feasibility of customising universal models towards various users, scenarios or contexts at a low computational overhead.

2.1.1.3 Network communications

As in the seamless background integration of voice analysis and similar acoustic methods, the in-built network communication capabilities of smartphones may also be used to extract meaningful data about users. For example, the outdoor behaviour of mental health patients has been shown to change according to their mental state [15, 129], allowing GPS tracking to provide insight into activity and mobility behaviours [15]. Although current GPS implementations appear to focus on risk management such as monitoring the location of vulnerable patients to prevent and deal with emergencies [130, 131], more data-driven uses for GPS in behaviour modelling have been suggested for future works, such as observing the amount of time spent indoors or outdoors, the distances a person has travelled, the frequency of visits to places of interest, as well as daily habits and consistency [15, 132].

WiFi may also be used in conjunction with such methods to establish indoor location more accurately, achieved by calculating signal strength for all visible access points, commonly referred to as fingerprinting [133–136]. Depression is one example of a condition in which patients commonly limit their activity radius to within their place of residence, and in severe cases, do not often leave their bed [129]. Utilising GPS and WiFi data, information may be analysed over time to find trends in various location behaviours, monitor progress and the impacts of treatment, or to make comparisons in the data, such as comparing morning and afternoon activity [134–136].

Bluetooth has similarly been used to classify the density of people within a small proximity of a user's phone, typically representing the amount of people that someone has been in the presence of, or alternatively, to determine if they are frequently alone [137–140]. Given that most people tend to keep Bluetooth enabled even when it is not in use [137, 138], previous studies have attained accuracies between 75% and 80% regarding crowd density, solely by scanning for visible Bluetooth-enabled devices [137–139].

2.1.1.4 Inertial sensors

Measures of physical activity are perhaps the most common uses for smartphone sensors, with a large number of studies employing various inertial sensors such as accelerometers, gyroscopes, and sometimes magnetometers to determine a device's motion, speed, direction and orientation [11, 15, 141–146]. Previous research has found correlations between physical activity levels and cognitive or mental state, particularly for the diagnosis of depression [15, 141, 144].

Smartphone sensors have been successful in monitoring activity levels over time to identify and predict a range of distinct conditions and their corresponding incidents, predominantly targeting depressive episodes [141, 142, 146], anxiety attacks [15, 142, 147], mood changes [141] or stress levels [11, 145, 148], as well as contributing factors such as sleep cycles and rest quality [144, 145]. In practice, such methods often sample and recognise patterns within the data, automatically producing user-friendly visualisations while also reporting results to clinicians, therefore allowing professional oversight and corrective feedback [11, 15].

While inertial sensors are typically combined to determine movement behaviours and activity, either with similar measurements or with distinct sensing types, it is also possible to employ low-power models that can correctly detect changes in aspects of mental health and wellbeing. Exclusively using a smartphone's in-built accelerometer, statistical models have been employed by Garcia-Ceja et al. aiming to perceive stress levels within a workplace environment, achieving 71% accuracy for user-specific models, and 60% for more general methods [11]. Such results are said to be comparable with state-of-the-art stress recognition systems in the field, with the distinction of relying solely on a single triaxial accelerometer sensor. Exploratory results found through the gathered data and subsequent analysis suggest that features from accelerometer data alone may be used as predictors in order to classify various levels of stress, and that evaluating behavioural inferences alongside physiological measures increases the accuracy of stress detection compared to using physiological features alone. Future work established by the authors includes the analysis of contextual situations in conjunction with their current models, for example, defining when and how a user is handling the phone during calls or when typing messages, which is hypothesised to allow more tailored and precise insights into user behaviours.

2.1.2 Biomedical sensors

As well as sensors usually embedded within smartphones, biomedical sensors – also referred to as wearable medical sensors – are gaining increasing attention from both industry and the scientific community, motivated by continuous advances in sensing abilities, wireless communication, and more recently, machine learning capabilities [8, 9, 12, 149]. Types of biomedical sensors range from simple heart rate monitors [150, 151] to intricate perspiration sensors [152], and through compatibility with the internet and other network connections, the potential of wireless sensors in monitoring personal medical data has extended beyond their traditional applications, with many data-gathering advantages similar to that of smartphones [12, 56, 149]. Heart rate monitors appear to be a popular and widely accessible choice throughout mental health intervention literature [8, 9, 12, 153, 154], and have been frequently combined with various other sensors such as eye tracking and camera recordings in order to detect and manage anxiety in seasonal affective disorder patients [8, 9, 12]. These studies regard wearable medical sensor devices to be a feasible and promising method of detecting anxiety, and in addition, as a means of enabling further action [8, 9, 12]. In the application of 'FaceIt' specifically, anxiety attacks detected by heart rate monitors allow an attached camera to start recording the situations causing such episodes, stored for later use within cognitive behavioural therapy sessions [9].

Sophisticated biomedical sensing modalities have also been applied to the area of loneliness, in which Feng et al. employ machine learning approaches to assist in decoding physical brain responses of loneliness from whole-brain resting-state functional connectivity (RSFC) [56]. Results found that individual-level loneliness can be predicted by within-network and between-network connectivity of various parts of the brain responsible for cognitive control, emotional processing, social perceptions and communication, where the prefrontal, limbic and temporal systems are noted as determining factors. Correlating with research widely established in loneliness literature, findings also prove that loneliness – and particularly, its associated neural substrates – is largely controlled by levels of neuroticism and extraversion [14, 55, 57–59], demonstrating the predefined importance of maladaptive social cognition as well as the divergence of loneliness between individuals and personality types. This study is considered an introductory effort regarding the individualised prediction of loneliness, intended for use in both diagnosis and treatment, and is also the first attempt to evidence predictive brain-based features of loneliness through analysing the structure within intrinsic brain networks.

While such advanced sensor systems have high potential in the detection and monitoring of various mental health disorders, it is evident that they often require specialist hardware that may not be commercially or even generally available, and are sometimes created manually by researchers as a result [56, 155, 156]. Given that biomedical sensors must always be attached to the user of interest, they are also deemed obtrusive and uncomfortable [10, 11, 15, 103, 104, 118], typically requiring a more complex setup such as specific bodily placement, which is commonly operated by experts [20, 56, 152]. For these reasons, it appears that many intricate biomedical sensors are limited to clinical environments.

2.1.3 Sensors in application to loneliness

State-of-the-art methods utilising either biomedical or smartphone sensors all demonstrate their effectiveness and potential in identifying and managing various mental health disorders, in which many behaviours such as those concerning inertial, biological, communicational and software-based attributes each have valid uses that are able to measure distinct characteristics of mental health conditions. From a review of current sensor practices, it is evident that sensors typically employed in smartphone devices express physical or external behaviours of users, such as their speech, movements or navigation patterns, whereas biomedical sensors measure internal bodily reactions, often involving the heart or brain. On the other hand, software sensing – while often carried out on smartphone devices, may also be performed on any platform that supports a user's frequently used applications such as social media – predominantly concerns psychological mental models and subsequent corresponding behaviours. Altogether, when used alongside machine learning and other data processing methods, such techniques utilising the data gathered from diverse sensor types may be suitable within loneliness interventions in a similar way, especially considering the inherent correlations between loneliness and many of the explored conditions, such as depression, anxiety and stress.

At present, software-based analysis appears to be the only smartphone sensing type used in experimental loneliness research, and there is much potential to be explored in terms of inertial, ambient and communication sensors that have been successful for the detection and monitoring of similar conditions. Regarding biomedical sensors, preliminary relationships between biological functioning and clinical loneliness have already been found through the analysis of brain responses, although other biometric features such as heart rate and eye tracking behaviours – perhaps those identifiable through more widely available sensing types – have not yet been explored. In this sense, for many measurable features of loneliness outside the subjective self-reporting methods currently used, there is limited evidence of what physically or biologically characterises loneliness, even though its psychological conditions, such as cognitive biases and maladaptive social cognition, are generally well-understood. Therefore, gathering sensor data from patients suffering with loneliness is essential in later stages of intervention development, which will allow training of machine learning models in order to produce AI systems that aid the classification and prediction of emotions, behaviours and patterns that assist in managing loneliness as a chronic state.

Therefore, personal sensing methods theoretically have the ability to improve upon the weaknesses posed by traditional loneliness interventions. While these improvements likely depend upon the practical application of sensor data, these capabilities allow personalised treatment through analysis of patients' individual data that reflects their physical and psychological behaviours, taking into account the diverse nature of loneliness as a multifaceted condition, along with the connections and relationships between these measured variables. Utilising this information, interventions targeting a change in implicit thoughts, behaviours and emotions negatively affecting one's condition may be carried out as opposed to more generalised methods that focus on objective social isolation.

2.2 Virtual reality

As well as the ability to analyse and identify contributing factors of various psychological conditions, the applications and interfaces that users interact with and experience as part of such interventions are particularly important within healthcare and wellbeing settings. A rapidly developing and highly prevalent field encompassing innovative interaction environments, which is increasingly deployed within many healthcare interventions, is virtual reality [157–161].

Although the initial hype of virtual reality in the 90s swiftly subsided due to a lack of adequate hardware and digital content [159, 160], the concept of immersive displays has been revisited over the last decade, receiving a new wave of enthusiasm through rapid advances in high-speed communication and computational capabilities [157–160], subsequently emerging as a sophisticated human-computer interaction platform, said to be approaching ubiquitous prevalence [157, 161].

Over the Covid-19 pandemic especially, virtual reality has played a critical role in social settings, allowing simulated face-to-face interaction with others during a time in which worldwide populations were required to remain homebound, while also minimising physical contact in order to reduce the spread of the virus [158, 159]. Taking inspiration from such increased interaction and its potential to enhance connections and communication between users, the application of virtual reality in a loneliness context may be beneficial to explore in detail, particularly with an intervention-based perspective regarding mental health conditions that are associated with subjective loneliness. While social emphasis is generally unsuccessful within traditional loneliness interventions [45, 50, 53, 87], the ability to apply any virtual experience and encourage particular behaviours through realistic interactions makes virtual reality an interesting prospect in relation to subjective loneliness, especially with the commonly expressed importance of personalisation and cognitive behavioural therapy [45, 50, 53, 55, 56].

Explicitly, virtual reality refers to an experience in which users, typically of a headset device that covers the eyes with digital screens, become immersed in a simulated 3D world that may be explored or interacted with, sometimes through dedicated controllers designed for use with a particular headset [162, 163]. By presenting the human senses with a virtual version of reality that can successfully synchronise its hardware and software components with implicit physiology, resulting sensory information sent to the brain may cause users to perceive it as a real environment through the illusion of presence, particularly when virtual interactions parallel those performed physically in real-time [20–25, 40, 162, 164]. Many researchers anticipate a prolific presence and adoption for virtual reality within a broad range of domains [20, 40, 162, 164, 165], and while research is a significant application of such technology, it has also become increasingly available in sport, training, education and entertainment, among many others [20, 162, 165].

Virtual reality holds many benefits that are not easily achievable through other means. For example, real-life experiences that are impractical, dangerous or costly may be carried out through virtual simulations that immerse users such that the experience reflects reality to a believable extent [20, 42–44, 162]. In this sense, taking risks in a virtual setting allows users to gain real-world skills, such as through pilot training [166] and virtual surgery operations [167], which correlates with the actions and behaviours needed in their corresponding real-life scenarios [20, 40–44, 164, 166, 167]. Similarly, the environment and immersive experience of a user such as what is seen, heard and interacted with may be completely or partially controlled by developers, ensuring the intended effects and impact within the particular virtual space [19, 20, 24, 40, 41].

Regarding academia, virtual reality technology has been established as a means of achieving high ecological validity in its ability to induce naturalistic reactions, especially compared to those received in traditional laboratory environments [40, 41]. As a result, this enables scientists to explore complex research questions that may be otherwise unsafe or infeasible. Virtual reality is consequently becoming a major research tool used around the world [20, 40, 162, 164, 165], however some researchers claim that a thorough understanding of why the technology is so effective, as well as its full effects on the human mind, has not been adequately explored [19, 164, 168–171]. Regarding this issue, the concept of presence is most established in current research, primarily attributing to the cognitive process of attention or mental models pertaining to a virtual space [20–25]. Fundamentally, presence is said to comprise of three factors – spatial presence in which one feels as though they are physically within the virtual space, involvement regarding the extent of focussed attention on virtual stimulus and dismissal of competing external factors, and lastly the level of realness, where the virtual environment and its interactivity coincides with expectations of real life [169–173]. By enhancing presence – that is, maximising each of these components – virtual reality has been associated with increased psychological arousal within several studies, allowing users to feel connected with the environment and, in the case of medical applications, improve their response to treatment as a result [19, 168, 172, 173].

In healthcare and wellbeing contexts, the two most researched application areas for virtual reality appear to be therapy in psychology and mental health domains, typically in the form of exposure therapy to combat anxiety and irrational fears, as well as pain relief through immersive distraction therapy. Given their success and extensive use, exploring such applications as well as the research and theoretical understanding that underlies various methods and decision-making processes is important to establish knowledge in virtual reality efficacy that may be applied in loneliness interventions.

2.2.1 Virtual reality in healthcare

Mental health is often said to be one of the most promising purposes of virtual reality within a healthcare context [19, 21, 32, 33, 35], and many studies utilise such applications for exposure therapy [19, 21, 24, 26, 27, 32–34], a widely used subset of cognitive behavioural therapy [21, 174]. During virtual exposure therapy interventions, patients are subjected to virtually-generated stimuli representing their fears or anxieties, providing an opportunity to disconfirm negative expectations regarding the presented scenarios [19, 24, 174, 175].

Using a virtual environment allows patients to be exposed to any and multiple contexts without leaving the therapist's office [19, 20], alternatively supporting treatment at home. The dynamic nature of virtual reality content is especially valuable in exposure therapy, in which therapists may control and manipulate the feared stimuli experienced by patients with much more ease compared to traditional, 'in vivo' exposure methods [24]. For these reasons, researchers and medical professionals identify virtual reality as an ideal and practical tool for exposure therapy applications [19, 21, 176].

Typical applications of virtual exposure therapy tend to focus on particular phobias, challenging irrational fears like heights [22], flying and spiders [33, 34], however anxiety disorders and similar mental health conditions are also frequently targeted in a number of applications [19, 21, 32, 177, 178]. In particular, one virtual reality application named Bravemind employs prolonged exposure therapy in the treatment of war veterans suffering with PTSD, immersing these users through convincing sensations that are associated with warzones and battles, primarily including explosive and unpredictable environments [32]. Studies utilising Bravemind with PTSD participants find that such methods are an effective form of treatment, proven to better patients' mental health to a larger extent than pharmaceutical alternatives while also highlighting a safe environment with negligible side effects [179–181].

Virtual exposure therapy has also been useful when treating public speaking anxiety and social phobia, shown to reduce symptoms among patients diagnosed with severe anxiety [19, 21, 33, 177]. Klinger et al. demonstrated that this decrease in symptoms is comparable with those receiving traditional conversation-based cognitive behavioural therapy treatment [177], while Anderson et al. demonstrates results highly successful in reducing public speaking fears [178]. For social phobia patients, interacting with a virtual audience is claimed to increase both arousal and anxiety within a virtual exposure therapy environment, known to be important factors of treatment success [19, 33]. Given that existing interventions for social fears involve the recruitment of audience members, potentially requiring a large number of people, virtually simulating such public speaking scenarios also helps to overcome a major barrier to treatment that is often faced through traditional means [176].

The importance of examining the aforementioned factors of presence is emphasised in several studies, predominantly those that focus on the treatment of anxiety conditions. For example, research shows that greater attention towards fear-based stimuli improves the effectiveness of exposure therapy treatment [19, 172, 175, 182, 183], whereas distraction from these stimuli hinders treatment response [19, 172, 175, 184]. Therefore, the involvement component of presence is important in a virtual reality environment and its ability to retain patents' attention, which enhances potential efficacy in an exposure therapy context [21, 22, 172, 175]. The realness factor of presence is additionally relevant for fear structure activation, representing the concept of how real or believable the virtual experience may feel [168, 174, 175, 185].

As a result, applying theories of presence has been identified as a technique by which virtual exposure therapy can successfully treat fears in a real-world context [21–25, 164, 170, 171]. Presence is primarily associated with the emotion processing theory, stating that presenting and embracing feared stimuli is essential in order to activate a psychological fear structure – including information about feared stimuli, fear responses, and the meaning behind these stimuli and responses – which is necessary for effective exposure therapy [174]. The theory also notes, however, that such fear structure activation does not guarantee the efficacy of exposure therapy in isolation. In this sense, applying such methods in a prolonged, repeated and controlled manner is required to increase validity, and consequently, for successful treatment to occur [19, 174].

Contradicting the emphasis of exposure, pain relief is another prevailing application of virtual reality systems, particularly in the ability to immerse users as a means of distraction. Studies find that by competing for attention between the perception of pain and the conscious focus on information processing activities, such salient sensations may not be perceived to the same extent, if at all [26, 28–31]. Utilising this knowledge, virtual distraction therapies have been widely explored throughout the research field, all with high success – virtual reality sessions have been shown to provide significant pain relief with an average of 66% pain reduction, persisting with a 45% reduction after virtual sessions had finished, lasting around 30 hours on average [28]. Other studies find comparable results, in which all participants of a study conducted by Jones et al. reported some degree of pain relief during virtual reality sessions, whereas a third described complete pain relief [31]. Furman et al. further finds higher levels of pain reduction through virtual pain relief sessions in contrast to traditional distraction techniques such as watching a movie, in addition to patient preferences regarding virtual reality sessions over such alternatives [30]. Similarly, Herrero et al. demonstrates significant increases in mood, positivity, motion and self-efficacy as a result of using virtual reality solutions [186].

Collectively, such findings establish high potential for virtual reality in the context of chronic pain management through psychological treatment, proving its immersive capabilities to an extent higher than traditional distraction methods. However, the application of this technology has also been proven to affect concurrent experiences such as perceived levels of self-control [187], as well as more long-term impacts on memory [30, 188], shown through studies on dental experiences. Using virtual reality distraction methods, participants with higher dental anxiety revealed a greater reduction in memory vividness than those with lower dental anxiety [30, 187, 188], significant given the negative experience that their dental procedures are likely to cause [188].

An additional longitudinal effect of virtual distraction therapies, particularly regarding pain relief, includes its alternative to pharmaceutical solutions that can outperform to opioid medication [31, 32, 188, 189], with a significant reduction in negative or harmful side effects as well as risk of addiction [31, 32]. Immersive distraction through virtual reality has been proven to significantly reduce the amount of medication administered during painful wound care procedures, where in one study, only 11% of participants requested more than one dose compared to 60% of those who went through procedures without virtual reality immersion [189]. As a result, these methods have been considered beneficial within cycles of iterative care, such that previous experiences affect treatment response and behaviour in future circumstances [188].

2.2.2 Virtual reality in application to loneliness

Virtual reality is evidently effective in application to healthcare and general wellbeing, with immersive capabilities that demonstrate high potential for inducing an enhanced state of virtual presence. Contrasting the identification of symptoms and behaviours often employed within sensor-based applications, virtual reality instead tends to incorporate elements of cognitive behavioural therapy and long-term confrontation of negative internal functioning, consequently overcoming detrimental habits with the intention of changing intrinsic behaviours. Given the importance of such methods established in loneliness literature, particularly as an alternative to interventions targeting social skills and events, virtual reality appears to be a relevant platform in application to loneliness, which has already been shown to produce successful results when utilised for conditions that inherently correlate with loneliness as a chronic state, such as those explored in application to social fears, anxiety and PTSD. However, while the social interfaces of virtual reality appeared to support communication with others over the Covid-19 pandemic, no applications specifically designed to address either subjective or objective loneliness have been found within the literature, indicating an importance and future requirement to explore this potential.

Regarding traditional loneliness interventions, virtual reality additionally has the capacity to overcome the commonly faced limitations highlighted in loneliness research, particularly concerning the ability to immerse users in an environment that, through exposure and guided interaction, encourages a change in the implicit behaviours and emotions that negatively affect perceptions of social relationships, such as maladaptive social cognition. Along with this augmented practical experience and self-educational training, the dynamic and controllable environment of virtual reality further allows personalised experiences that are typically controlled by professionals, designed according to the needs and contexts of users on an individual level. As such, this individualised focus on adapting the internal and personal issues of loneliness provides a more effective and long-term intervention strategy than the generalised, 'one-size-fits-all' methodology of increasing social interaction that is commonly used in treatment.

Despite the precise control of a patient's external experience, however, insight into the internal experience remains unseen due to a lack of understanding regarding physiological and emotional responses. Recently, researchers have begun to combine the use of existing sensor technology to capture measurements of behaviour and internal response that occurs within virtual reality experiences [20, 32, 36, 37, 68, 69], enabling data collection that is typically used to train machine learning classifiers [20, 190]. The potential uses for such applications are vast, particularly considering the effective results found in research employing sensor data for the identification, treatment and management of various mental health impairments, along with the use of technology that is able to immerse users within versatile and controllable environments through a convincing sense of presence, proven to be effective in both physical and psychological control for the management of various conditions.

In this sense, the concept of combining such technologies holds high capabilities in regard to loneliness as well as in general health and wellbeing, and so the exploration of research and state-of-the-art applications utilising these disciplines collectively is vital in the assessment of its potential application, additionally influencing the future development of effective innovations in managing loneliness.

2.2.3 Sensors in virtual reality

The combination of virtual reality and personal sensing data is a newly accelerating field, particularly with the increasing affordability and wide adoption of virtual reality systems in diverse areas such as healthcare, education and business [20, 32]. Analytics involving user attention and focus is a common, more general application of sensor data that allows UX designers to plan and create experiences influenced by users' reactional feedback, and connecting this attention data to measurements of a user's reaction then supports understanding of their responses to a greater extent [20, 36, 37, 68]. Eye tracking is a conventional method of capturing such data[1,2,3,4] which, for instance, allows identification of a user's focus, as well as which features produce the most positive or negative reactions through additional biological sensors such as heart rate monitors[1] [20, 36, 37, 68].

The majority of existing applications employing personal sensing within virtual reality contexts emphasise the role of emotion or cognition in analysing psychology, behaviour or an experience[1] [20, 68]. Some virtual reality gaming platforms have started to introduce simple sensor data that influences game situations in order to personalise the experience,

[1] https://www.hp.com/us-en/vr/reverb-g2-vr-headset-omnicept-edition.html
[2] https://business.vive.com/uk/product/vive-pro-eye-office/
[3] https://www.picoxr.com/us/neo3.html
[4] https://varjo.com/products/vr-3/

primarily based on each player's physiological state [32, 191–193]. The first of these games – namely regarding its sequel containing many technical upgrades, supporting virtual reality in later stages – was called Nevermind, described as a "biofeedback-enhanced adventure thriller game" that assesses and responds to levels of stress or fear, altering various aspects of gameplay such as difficulty with the intention of challenging players to overcome their fears by improving their emotion regulation skills [193].

A large number of off-the-shelf sensors are compatible with its emotional state detection algorithms, such as heart rate monitors, eye trackers, as well as basic webcams that employ facial recognition for emotion detection, and while each individual sensor provides an accurate experience in itself, combining these sensors is said to provide an extremely responsive biofeedback experience that reacts to players in the most appropriate way. Nevermind has been utilised in various scientific studies, exploring its ability to induce serenity [194] or stress [195], improve interoceptive awareness [196], encourage engagement and enhance usability from a design perspective [196–198], along with many more applications. Typically its performance and anticipated future potential is high, and such innovative methods have been considered an entertaining and rewarding method of user analysis through successful results in the research community [193, 195–198]. In this sense, similar applications may be applicable in an adaptive and personalised cognitive behavioural therapy context that takes the multidimensional nature of conditions into account.

In the fields of healthcare, mental health and general wellbeing, real-time insights into virtual reality experiences have also proved beneficial for biofeedback, the assessment of conditions or patient progress, and for methods of treatment personalisation[1] [20, 36, 68]. Combining virtual reality therapy in the treatment of patients, alongside its natural collection of personal sensing data, has been applied to determine the progress and effectiveness of treatment for phobias [36, 193] and other mental health conditions like PTSD [37]. Through these studies, headsets designed by behavioural health technology specialists Amelia[5] – a company providing virtual reality platforms with embedded sensors, primarily aimed at healthcare professionals – are applied in various anxiety and phobia scenarios, commonly including the system's pre-prepared environments, such as

[5]https://ameliavirtualcare.com/

ones designed for patients with agoraphobia [36].

During these studies, an electrodermal sensor is fitted to participants' fingers to measure galvanic skin response which, through further data processing, may be used to calculate subjective units of anxiety that can be monitored throughout exposure to virtual environments inducing such anxiety. Utilising these methods for patient monitoring and subsequent personalised treatment, results demonstrate the ability to clinically improve patients' conditions, with reductions in measurements of both galvanic skin response and subjective units of anxiety [36, 37]. These results are found to be comparable across similar areas of mental health literature, and in particular, Zhang further suggests that using such methods to combine elements of cognitive behavioural therapy, exposure therapy and eye movement desensitisation and reprocessing (EMDR) improves their respective weaknesses, such as the inefficiency of conversation-based therapy, the complexity of clinicians' preparation regarding the diverse and holistic nature of conditions, potential detrimental effects of inaccurate patient evaluations such as misguided prolonged exposure, and the ineffectiveness of building upon a relaxed state in pursuit of successful treatment [37].

Similar to Amelia technology, unique virtual reality devices have been created for industrial and academic development of behavioural tracking systems, including a variety of embedded sensors to facilitate the detection of user responses to virtual content, therefore enabling more adaptive and personalised experiences that may be designed through user participation and data-driven approaches[1] [20]. HP's Reverb G2 Omnicept integrates sophisticated machine learning models with data gathered from eye tracking, pupillometry, heart rate and facial camera sensors, providing access to abstracted processing techniques through predefined programming interfaces that allow developers to utilise gathered data without having to implement their own models from scratch[1]. At a smaller scope, the Vive Pro Eye[2], Neo 3 Pro Eye[3] and Vario[4] headsets all have in-built eye tracking capabilities, predominantly intending to capture users' interests regarding the areas they focus on.

Targeting mental health applications specifically, the emteqPRO developed by Gnacek et al. aims to provide an all-in-one solution that has access to several distinct sensor types, specifically referred to as a multi-sensor array, aiding the collection of inertial, biological and psychological data that has been empirically proven to be important in the study of human emotion and behaviour [20]. Built into faceplates designed to fit into a number of popular virtual reality headsets, the multi-sensor array includes an eye tracker and pupillometry sensors, a heart rate monitor with heart rate variability, an inertial measurement unit that tracks various movement features such as force, angular rate and body orientation, a photoplethysmogram (PPG) that detects blood volume changes within facial tissue, and an electromyography (EMG) sensor to evaluate electrical activity in facial muscles, stressed to be particularly important in the role of detecting emotion [37, 199–201]. Ease of use was a main factor prioritised in the technology's design, reducing unnecessary complexity regarding intrusiveness for users and the onerous setup of external sensors, while also enabling a simple integration process for hardware sensors and software engines.

Figure 2.1: emteqPRO mounts for the HTC Vive Pro (left) and Pico G2 4K (right) [20].

Through the capture of heart rate and eye tracking features, along with skin impedance, facial muscle activations and physical movement data, a number of studies have employed the emteqPRO in the detection of arousal and valence changes [202–205], although its applications in the area of mental health and wellbeing appear to be limited despite its potential and original intention.

2.3 Literature review summary and conclusion

To summarise, hardware sensors and virtual reality are individually beneficial for distinct aspects of managing mental health. Personal sensing is particularly valuable in the autonomous collection of a user's data, which may concern various types of information such as inertial, biological, communicational or software-based. Such information is typically utilised in the identification and prediction of behavioural patterns relating to a specific condition, interpreted from these underlying sensor readings through machine learning and various data processing methods. While different categories of sensors each have distinct intentions and common uses, the importance of incorporating users' individual characteristics into interventions has been emphasised within the literature, allowing more personalised treatment as well as an insight into the critical relationships between a condition's associated variables.

Conversely, virtual reality provides an immersion and sense of presence that is uniquely possible through this technology, commonly associated with increased psychological arousal through connectedness within a virtual environment. With this perception of reality, such applications are crucial in the context of cognitive behavioural training and distraction, granting physical, real-world experience within controllable virtual environments in order to confront internal psychological issues, additionally targeting a long-term change in behaviours that are detrimental to one's physical or mental health.

In relation to the aims of the project, both virtual reality and personal sensing technology have demonstrated high suitability in their application to loneliness interventions, especially given the success during studies examining conditions and behaviours that also characterise and correlate with subjective loneliness. However, combining such technologies further increases this potential, and not only allows the collective advantages of personalised, multidimensional treatment that addresses the internal source of negative behaviours, but also augments each beneficial factor, such as allowing virtual reality environments to adapt to user reactions, or to induce psychological states through virtual situations in order to analyse a user's subsequent response. Existing studies utilising these systems have been proven valuable in various applications, however regarding loneliness literature specifically, the effectiveness of controlling maladaptive internal cognition compared to other intervention strategies, in addition to the emphasis of personalisation and the diverse structure of loneliness and its causal relationships, establishes that utilising both virtual reality and personal sensing within an intervention system certainly has the capability to provide purposeful and effective support for those suffering with loneliness. In this sense, the three weaknesses identified within traditional loneliness interventions have the potential to be improved upon with such systems.

As such, a comprehensive review of literature in this area concludes the high potential of virtual reality environments, able to analyse and adapt to user behaviour by utilising individuals' sensor data, in the context of loneliness interventions as well as in addressing the limitations faced in the traditional approaches most commonly used. By employing the success factors of effective related works, such as the personalised identification of behaviours and an authentic sense of presence, an application that fully embodies these concepts shall be developed in relation to loneliness, implementing an immersive cognitive behavioural training experience that recognises and subsequently adapts to user responses based on real-time sensor data, therefore providing the most appropriate feedback.

Chapter 3

Planning and project management

To achieve the second aim of the project, development of a system incorporating virtual reality and sensor technology is accomplished in accordance with the values and approaches discussed within evaluation of relevant literature. Various research and planning stages took place throughout development, ensuring that design and implementation effectively integrates the significant concepts discussed. As such, important components of planning include the hardware and software tools utilised, the employed development life cycle and resulting timeline of implementation structure, as well as predefined risk mitigation strategies regarding efficiency and completion of development.

3.1 Choice of hardware tools

To ensure adequate fulfilment of the advantages seen in previous studies, including those utilising both sensor data and virtual reality, a review of present hardware tools able to produce relevant, valuable data and immersive capabilities first needs to be reviewed. Firstly, three categories of virtual reality devices currently exist, namely those that are handheld, allow head-mounted smartphone attachments, and ones that possess more sophisticated designs, with in-built computers and specialised screens situated for each eye [206–208].

While handheld devices like the Google Cardboard are the most affordable and widely produced[6], they lack head-mounting apparatus and therefore require constant positional

[6]https://arvr.google.com/cardboard/

support, and so applications are often limited to simple orientational controls given that users must hold the device at all times, which prohibits the use of external controllers. For these reasons, such devices are typically regarded as most suitable for minimally interactive short-term experiences, such as watching a music video [206–208], and are unlikely to provide the immersive experience and sense of presence required within mental health interventions, particularly for extended use.

Head-mounted smartphone attachments are similar to handheld devices in terms of performance capabilities, with the added freedom of hands-free interaction through secure strap fittings. Many of these devices are used with external controllers or accessories such as Bluetooth gamepads[7] [206], consequently allowing various types of applications and use over prolonged periods of time. However, these devices are limited to the hardware and software capabilities available in a user's personal smartphone, which most importantly provides minimal immersion through an unadaptable phone screen that is not specialised for virtual reality.

Subsequently, computer-integrated head-mounted displays appear to be the most suitable choice for this project, with hardware and software components built specifically for virtual reality environments. These systems offer much more robust and immersive virtual experiences [206–208], supporting high-fidelity graphics and a range of input devices, typically employing dedicated controllers designed for use with a particular headset. With the ability to track a user's position in space through various in-built sensors, these devices provide an increased sense of presence through consistency of expectation, mapping physical movement to equivalent interactions within the virtual world.

Several virtual reality headsets with these capabilities exist, however the Oculus Go in particular is a simple, lightweight device requiring no external wires to operate[8], which is particularly beneficial in an intervention context. As such, users are relieved of physical discomforts such as heavy and bulky hardware or intruding and restricting wires, improving the overall experience as well as contributing greatly to factors of immersion and presence. While newer headsets such as the Oculus Quest are said to be of a higher quality with improved resolution, field of view and tracking capabilities

[7] https://www.ultraleap.com/product/leap-motion-controller/
[8] https://www.oculus.com/go/features/

[206–208], the lightweight and compact nature of the Oculus Go may be more important than these technical enhancements, especially given the minimal technical requirements of this preliminary research.

Figure 3.1: Oculus Go virtual reality headset[8].

Regarding hardware sensors, many of the biomedical sensors explored within relevant literature have great potential in the measurement of loneliness and general mental health conditions, however with the limited timeframe of this project, smartphone sensors were much more accessible in comparison. Such sensors, universally embedded within everyday smartphone devices, have proven successful in their application to the monitoring, identification and management of various mental health disorders, providing a range of sensing modalities within a single device. For this project specifically, data gathered from preliminary user studies further indicated suitability of a smartphone's gyroscope in particular, found to produce the most appropriate and valuable information when representing the required types of user behaviour.

Similar to the advantages of the lightweight and wireless Oculus Go, smartphones also require no external connections, and can be used to seamlessly collect data even within the user's pocket. As a result, smartphone sensors provide better comfort and familiarity that minimises the observer effect during studies [10, 11, 103, 104], proven to reduce the stress of monitored patients [105] and further improve adherence and compliance [15, 106–109]. Utilising such combinations of convenient and unobtrusive technology aims to enhance user experience compared to that of more conspicuous accessories, as well as potentially improving the quality of results through unhindered interaction.

3.2 Choice of software tools

Much of the documentation for Oculus Go development, as well as for virtual reality in general, highly recommends the Unity game engine, including the Oculus website itself[9]. Unity is commonly known as the leading game engine worldwide[10], and although it is primarily designed to aid the development of games, it can also be utilised in the creation of virtual reality applications.

Most Unity versions are compatible with plugins for Oculus support[11], featuring a range of predefined, reusable tools and resources that make virtual reality development significantly faster than programming such applications from scratch. Given Unity's inherently available tools for Oculus development, as well as the extensive documentation and community support for Unity in general, it appears to be an optimal software development choice for this project.

The Oculus Integration package was deemed valuable throughout project development, providing practical tools and reusable scripts that allowed for a fast and efficient implementation of Oculus-related functionality that would have taken much longer to develop in a primitive manner, especially considering the requirement of a detailed, low-level understanding of Oculus hardware and its associated development. In this sense, having a working development environment for Oculus functionality enables a development style similar to that of other platforms, for instance, incorporating a predefined camera component that manages virtual visibility according to all hardware integrations in the headset, which may be substituted for the default camera component used within most Unity environments.

As a result, the workload of this project was substantially reduced, allowing more progress to be made in terms of intervention-based functionality and subsequent user studies.

[9]https://developer.oculus.com/unity/
[10]https://unity.com/
[11]https://assetstore.unity.com/packages/tools/integration/oculus-integration-82022

Given the project's focus on evaluating virtual reality and sensor technology in loneliness interventions – namely, creating a prototype application that may demonstrate successful intervention concepts, rather than the low-level implementation details themselves – the use of Unity and its Oculus Integration package was vital for the success of this project, enabling more focus on the theory and application of these methods.

Further benefits of Unity include access to the Unity Asset Store[12], in which any free assets such as audio, textures and 3D models can be downloaded and imported into the project at any time. While being able to use and choose from predefined resources greatly saves time compared to manual creation of these assets, it is also likely to improve the quality of the final product, given that many of these assets are professionally made.

3.3 Software development life cycle

For efficient development of the full virtual reality application, an agile methodology was adopted with an iterative and incremental approach, enabling foundational features of the software to be implemented quickly and then built upon during each iteration. In this way, new features were continuously added to existing functionality, while refining those previously implemented when necessary.

The complete development structure involved three main sprint stages, in which client and server sockets were first set up to manage wireless connections between smartphone sensors and the Oculus Go headset, next creating a fully functioning virtual reality game utilising controller-based inputs, and finally implementing a version of the game that is able to react to incoming sensor data through predefined socket functionality. Each of these steps was deconstructed into sprints relative to the widely recognised scrum framework, where workload is organised within a limited timeframe for each iteration, subsequently assessing the current progress and further steps towards completion in conjunction with the overall requirements at the end of each sprint [209, 210].

[12] https://assetstore.unity.com/

SPRINT TASK	TASK START DATE	TASK DURATION	SPRINT DURATION
SPRINT 1: CLIENT-SERVER SOCKETS			
Create Python client socket (PC)	11/07	1	3 days
Download and test Android server apps (phone)	12/07	1	
Test data streaming and format (phone to PC)	12/07	1	
Create C# Unity client socket (PC)	13/07	1	
Test data streaming to Unity (phone to PC)	13/07	1	
SET UP OF UNITY			
Download and install SDKs and plugins	15/07	6	15 days
Set up Oculus Go Unity environment	17/07	10	
Research and debugging	17/07	10	
Test build to Oculus Go	28/07	1	
Test data streaming to Oculus Go (phone to VR)	29/07	1	
SPRINT 2: GAME FUNCTIONALITY			
Cursor functionality with interactable objects	01/08	1	3 days
Apply pointer and reticule graphics	01/08	1	
Spawn enemies within bounds	02/08	1	
Create enemy targeting and shooting behaviour	02/08	1	
Destroy enemies on controller shoot	02/08	1	
Create damage and health system	03/08	1	
Update game UI canvas and functionality	03/08	1	
Create menu and state transition functionality	03/08	1	
Usability and aesthetic improvements	03/08	1	
Functional and end-to-end testing	01/08	3	
SPRINT 3: SENSOR INTEGRATION			
Data-gathering user study	05/08	1	3 days
Plotting and analysis of user study data	05/08	1	
Add audio effects	06/08	1	
User feedback adjustments	06/08	1	
Create separate scene for sensor functionality	06/08	1	
Generate dummy sensor data	06/08	1	
Identify slowed movement through value range	06/08	1	
Change difficulty state based on sensor data	07/08	1	
Create UI sensor state visualisations	07/08	1	
Substitute dummy data for gyroscope data	07/08	1	
Final testing and adjustments	05/08	3	

Table 3.1: Table of scrum sprints.

Development was initially scheduled over three consecutive weeks, however with some issues in setting up a working Oculus Go development environment, these stages were later split up into temporally separate blocks, with the second sprint taking place two weeks after what was originally planned, followed immediately by a small data-gathering exercise and the resulting final sprint. Despite these setbacks, each sprint's workload was completed earlier than the intended seven-day week, and so minimal time was lost by re-evaluating requirements according to the overall time remaining. As a result, each sprint lasted three long days, allowing extra time for research and learning before each cycle, with some additional time remaining for final updates, integrating necessary refinements and improvements to the existing functionality such as visuals, audio and user interaction. Significant progress had been made within a short period of time, employing full development of a gamified intervention strategy for loneliness through virtual reality and its sensor interaction functionality.

Given that the scrum framework is designed to significantly increase productivity [210], this style of structure was particularly helpful in completing work at a quicker rate, and with continuous stages of reviewing and planning at the end of each sprint, management of a potentially complex project was much more consistent. Such management strategies were also vital to ensure that the original aims and specifications regarding development were continuously upheld, therefore maintaining the values and techniques that drive the motivations of the project, such as those seen in the literature.

Comparably, Unity's Oculus Integration allowed quicker implementation of applications with common virtual reality functionality, and so use of this package within a scrum-style methodology supported the efficiency of development such that the combination maximised productivity.

3.4 Risk analysis

Several risks were anticipated throughout the project, and so for each of these risks, predefined mitigation strategies were created in preparation for their resulting circumstances. Both general and more specific project-related risks were included, identified as follows.

RISK 1: ***Planning and time management.***

Various external, project-related or personal interferences might have hindered the development of the project. Given the uncertainty and potential unavoidability of such contingencies, management-based mitigation strategies had been considered, such as reducing the length of each scrum sprint, reducing workload by excluding certain features of the application, or re-evaluating the project in worst-case scenarios. Sprint timeframes had initially been planned with longer time buffers than likely necessary, which allowed for flexible rescheduling in the case of development hindrances.

RISK 2: ***Loss of data.***

The risk of losing data, and therefore valuable progress, is relevant to any software development project given the dependence on both security and storage integrity. However, the use of backups and version control is common in such environments, and so a reliable mitigation strategy of data loss is the continuous backup of working software additions, typically to an online platform like GitHub[13]. While this allows recovery of corrupted or damaged files, it also enables a safe development structure in which invalid development changes may be reverted, providing access to the most recent functioning state. Given that no personal or sensitive information is included in the implementation of this project, uploading such data is deemed appropriate.

RISK 3: ***Issues with Unity or Oculus development.***

Past experiences with Unity and its setup with external devices have proved its difficulty in various scenarios, driving a number of safeguarding strategies similar to those relating to planning and time management. While management-based mitigations such as reducing workload and sprint timeframes are effective in reducing these issues, the additional assistance of specialist support was available through technical staff and lecturers if required, ensuring more reliable development if technical issues were to occur.

[13]https://github.com/

RISK 4: ***Suitability and robustness of hardware.***

Given the project's reliance upon both the Oculus Go headset and smartphone sensors, these hardware elements must be suitable in relation to the overarching aims and concepts of the project, as well as providing robustness that allows successful use of the application for user studies. To mitigate potential issues, several other technologies were made available for development in case of unsuitability, and particularly regarding the stability of connection between the headset and streamed sensor data, extensive testing and evaluation processes had been incorporated within the scheduling structure of development and project management.

RISK 5: ***Accuracy of concept representation.***

One of the most detrimental risks regarding outcomes of the project would be inaccurate or unrepresentative implementation of its intended purpose. Mitigation strategies were planned in relation to the literature as a result, ensuring a cyclic evaluation of loneliness as a chronic condition, successful related work, and the motivations and objectives of the project, throughout each stage of development. Such strategies guaranteed that all progression incorporated the values and concepts that the project intends to represent, minimising the risk of inaccurately implementing, for instance, methods of cognitive behavioural training, which could be harmful to participants, evaluation results and the project outcomes themselves.

RISK 6: ***Ethics and security.***

Ensuring high ethical standards is essential given the human-centred nature of the project. Regarding development, no elements of the created software were expected to cause physical or psychological harm, and participants using the system may withdraw at any time. Externally-reviewed ethics forms had also been carried out, ensuring the application and its uses were ethically fit for purpose. Security was considered in that gyroscope data is used in real-time and not stored at any point, however all such data is anonymised and further contains no personal or sensitive information.

Of these six risks anticipated, two were encountered over the development of the project. Given its older model, development support for the Oculus Go had lately been deprecated, and so only earlier versions of Unity were compatible with the device, together with a specific combination of SDKs, Visual Studio versions, and archived Oculus Integration packages. With these initial difficulties in setting up a working development environment through this deprecated support, both the 'planning and management' and 'issues with Unity or Oculus development' risks were dependent on each other, and their respective mitigation strategies were enforced as a result.

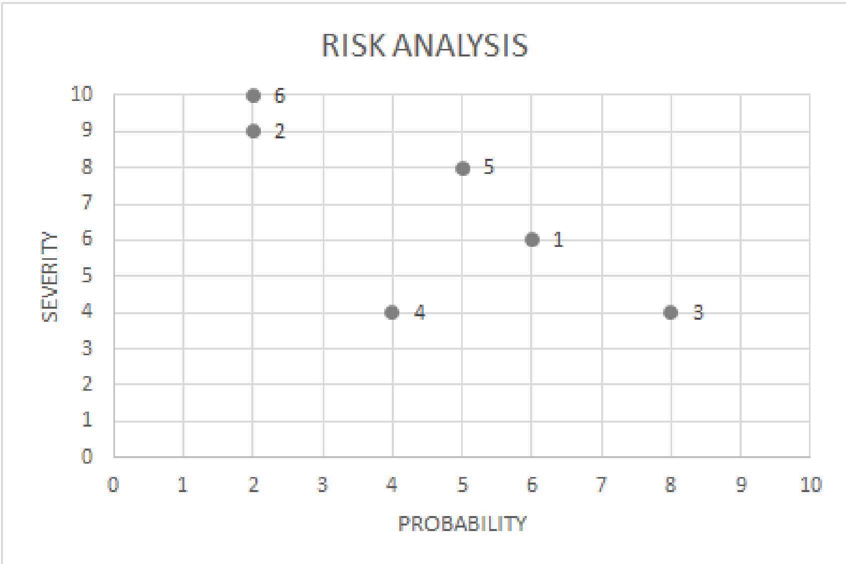

Figure 3.2: Scatter graph denoting the severity and probability of anticipated risks.

Although specialist staff support was not utilised, management-based mitigation was employed in terms of reducing scrum sprint timeframes through a continuous review of development requirements in relation to the overall time remaining. Given the initial time buffers integrated into the schedule, reducing these timeframes while retaining the same workload was still manageable, and so development was completed at a quicker rate. As these risks were previously anticipated and respective mitigation strategies were created in advance, adjustments were conducted without the need for additional preparation. In this sense, being aware of such potential risks significantly minimised the amount of time lost towards development.

Chapter 4

Design and implementation

Given the defined development process and management strategies undertaken, details regarding design and functionality of the developed system, including its essential requirements and programmatic implementation processes, are demonstrated in relation to its purpose and underlying functionality. Such functionality is justified through design decisions and practicality alongside the comparison with, and implementation of, concepts explored and evaluated within related works and the overarching literature.

4.1 Project definition

Explicitly, the developed project employs a game-based cognitive behavioural therapy approach to hypervigilance – a common "panic-like" symptom of loneliness in which one continuously anticipates and prepares for social threats [45, 53, 63, 211] – where gameplay difficulty adapts to user behaviours through a smartphone's gyroscope data, located within the user's pocket while using the headset device.

Hypervigilance is a biological adjustment to severe stress, often associated with a heightened state of alertness where one attempts to remove themselves from potential harm by preparing for threats in other people and the environment [45, 53, 63, 211–213]. Such symptoms are common in various conditions such as anxiety and PTSD [211, 212, 214] as well as subjective loneliness [45, 215], typically leading to avoidance of social interaction [212, 215], tension within relationships [212, 213], and reductions in trust [212]. In this sense, worst-case scenarios are often the ones anticipated, causing an impulsive preference for solutions that appear to promise the most immediate relief [215] – for example, this may include choosing to stay isolated from others in the case of loneliness, as opposed to triggering potentially uncomfortable or threatening situations involving social interaction. These behaviours are known to be exhausting for individuals afflicted with hypervigilance, altering psychological processes and cognitive functioning [45, 53, 63], reducing sleep quality [45], and subsequently escalating morbidity and premature mortality through weakening of the immune system [14, 45, 53, 56, 57, 60, 73, 77–79]. Commonly, hypervigilance causes an increased risk of heart disease and strokes as a result [14, 50, 53, 57, 60, 73, 77, 78].

Methods of cognitive behavioural therapy, including prolonged exposure therapy, are found to be most effective in treating hypervigilance [45, 53, 212], encouraging behavioural strategies such as deep breathing and meditation [212]. To demonstrate these approaches in a gamified virtual reality environment, hypervigilance is first represented by enemies spawned in random locations around the user, denoting threats that are anticipated in a typical environment. While enemies fire missiles towards the user, the user may also shoot spawned enemies with a dedicated virtual reality controller in the style of a first-person shooter, with the ability to dodge incoming attacks through physical movement. Incorporating mechanics of deep breathing and meditation, a slowed user state – arising with a change in movement behaviours – is measured through an external smartphone's gyroscope data, which prompts easier gameplay by reducing enemy spawn and missile rates, as well as missile speed. In this sense, the application intends to reward such responses within a simulated hypervigilance environment by demonstrating beneficial outcomes, encouraging an inherent change in behaviour when users become overwhelmed.

Development focussed on a surface-level implementation of hypervigilance concepts, simulated within a virtual environment that may measure and adapt to user reactions and behaviours in a way that, over time, would intend to change such behaviours with a cognitive behavioural training approach. Game-based treatment appears to be non-existent within loneliness literature, and so the application proposes a stimulating and enjoyable intervention strategy that motivates patients to take an active role in their treatment, especially given the current inaccessibility of interventions regarding their lack of incentive or inspiration, as well as perceived social stigmas [57]. Considering the game-based virtual environment is largely unrelated to hypervigilance experienced in real-life scenarios, instead employing functionality that is common within existing games made for entertainment purposes, negative or harmful reactions to such exposure are intentionally minimised.

Accordingly, the advantages of immersion, perceived presence and personalisation of experiences may be applied through use of virtual reality and sensor technology, additionally aiming to demonstrate resulting potential in its ability overcome the shortcomings of traditional loneliness interventions. Rather than intending to solve loneliness or related hypervigilance symptoms, the system instead aims to establish a proof-of-concept prototype that demonstrates use of such technology in application to loneliness concepts, including purposeful implementation of sensors and virtual reality functionality that may either encourage more productive research in this area, or be expanded upon through future work.

4.2 Application and integration of system

A future, more robust and meaningful implementation of such a system aims to be applicable in a clinical scenario with patients who experience chronic loneliness, as well as in more independent methods of treatment through self-management at patients' homes. In this sense, the application may be used within or in place of typical cognitive behavioural therapy sessions, allowing real-time feedback to both patients and clinicians regarding internal responses or external behaviour emerging from induced virtual stimuli.

As such, the application builds upon current work in sensor data processing literature, where behaviours relating to loneliness and resulting treatment response may be analysed in real-time to provide personalised and multidimensional feedback, particularly indicating patterns and trends in a patients' condition or state. The real-world application of this system also pertains to virtual reality research in its implementation of adaptive and immersive experiences that have the potential to change intrinsic behaviour and cognitive functioning. Therefore, future developments of the application and its corresponding research domain fulfils the current lack of such technologies in their employment for loneliness treatment, aiming to improve the understanding and efficacy of care for those suffering with loneliness.

4.3 Analysis of requirements

A number of requirements had been originally specified, significant within both the design and development stages of the project, to ensure an accurate implementation of concepts according to the literature, as well as the completion of a functioning application. Specifically, these conditions may be defined in two categories – functional requirements represent explicit interactions and functionality that the system must serve, whereas non-functional requirements denote the quality of attributes that judge the system's efficacy, typically assessed through testing and user studies.

Given the application's design concepts, the game-based approach to cognitive behavioural training for hypervigilance must fulfil the following functionality in order to produce a working prototype.

FR 1: ***Continuously spawn enemies in random locations around the user, within certain bounds.***
FR 2: ***Allow user interaction in which the Oculus Go controller can be used to aim and shoot at enemies to destroy them.***
FR 3: ***Ensure enemies continuously shoot back at the user while active.***
FR 4: ***Implement a health bar mechanic through collider hitboxes on both the user and enemy missiles, where users lose health each time they get hit by enemy fire and receive a game over screen when health reaches zero.***
FR 5: ***Include client and server sockets to manage a data-streaming connection between the Oculus Go headset and an external Android smartphone.***
FR 6: ***Implement an automated response to streamed smartphone data such that a meditative user state consequently slows enemy spawn rates and missile speed.***

In terms of judging the operational outcomes of the application, the next set of requirements define the attributes that must be achieved in order to fulfil its intended purpose.

NFR 1: ***Provide an enjoyable user experience to encourage positive attitudes towards treatment, and contribute towards behavioural change.***
NFR 2: ***Induce a sense of immersion and perceived presence.***

NFR 3: ***Adequately represent and demonstrate cognitive behavioural therapy concepts within a sensor-adaptive virtual reality environment.***
NFR 4: ***Employ purposeful and practical use of sensors and sensor data that influences the application in a meaningful way.***
NFR 5: ***Ensure the application runs smoothly such that it is not difficult or inconvenient to use.***
NFR 6: ***Ensure the application functions correctly, without bugs or errors.***

In terms of project completion, all functional requirements have been met solely through implementation. However, while non-functional requirements cannot be assessed through development alone, some may be evaluated through testing that is carried out during development. Specifically, this includes ensuring the application runs smoothly such that it is comfortable to use, and that it functions without any bugs or errors.

Remaining requirements relate to the effectiveness of the system when applied to hypervigilance-related cognitive behavioural training, and may be used as a means of evaluation when performing user studies that explore whether sensor data and virtual reality can be beneficial in practice, and have the potential to change user behaviour. At this development stage, eight of the twelve requirements have already been met.

4.4 Implementation and testing

As described in the employed software development life cycle, implementation phases had been separated into three functionality-related procedures, starting with the wireless transmission of sensor data between an Android smartphone and the Oculus Go headset. Following the setup of a working development environment in Unity, the implementation of foundational game functionality was completed within a virtual reality environment, lastly finalising the combination of the previous two phases by incorporating transmitted sensor data into the behaviour of the application. A small study on the analysis of sensor data, utilising a version of the application without sensor functionality yet built in, was carried out with a small number of participants in order to evaluate the suitability of various sensors and data processing techniques in application to the project. This data was collected during the final phase of development, used towards the implementation of sensor-based mechanics.

4.4.1 Client-server sockets

A substantial amount of research was conducted in search of appropriate wireless data transmission methods, particularly regarding implementations compatible with Android and Unity, and results often indicated the optimal suitability of client-server sockets. Given the availability of various Android applications for streaming sensor data, retrieval sockets were first implemented in a simple Python environment to test the utility of these existing applications. Several solutions were attempted, however most applications were found to be incompatible, either due to minimally customisable streaming options, or through broken features that were necessary for the needs of the project. A suitable application was eventually discovered, however, in which established connections between the two devices were accurate in their communication of sensor data[14].

```python
import socket
import sys
import ast

s = socket.socket(socket.AF_INET, socket.SOCK_STREAM)
s.connect(('', 5555)) #removed IP address

def getSensor(data, item):
    return str(data[item]['value']).strip('[]')

while True:
    data = s.recv(1024).decode('utf-8')

    if (not data.startswith('[')) & (data != ''):
        data = ast.literal_eval(data)
        print('\nacc: ', getSensor(data, 'accelerometer'),
              '\ngra: ', getSensor(data, 'gravity'),
              '\ngyr: ', getSensor(data, 'gyroscope'))
    else:
        s.close()
        sys.exit('Server connection lost')
```

Listing 4.1: Client socket receiving data from smartphone server.

[14]https://github.com/yaqwsx/SensorStreamer

Specifically, the implementation of data retrieval first included defining the socket as an object, subsequently connecting to the smartphone server represented by its IP address and port number. Given a successful connection, data streamed from the server is received through the socket within a continuous loop and stored as a JSON dictionary variable, allowing individual sensor values to be accessed and utilised through their corresponding index attributes. When the connection is lost or interrupted, the retrieval loop is broken and the program terminates accordingly.

Testing primarily concerned the format of streamed data and corresponding processing methods, along with various client-server setups and the stability of prolonged transmission over a range of packet speeds. Specifically, a form of black box testing was performed on streamed data to ensure that the implemented processing methods produce the expected output in terms of the data's JSON formatting and accessibility, while endurance testing included long periods of continuous streaming, for up to an hour at a time, to ensure the consistent and accurate transmission of this data. Such methods were conducted using a variety of packet speeds, in which all available speeds - including the highest possible speed of 200ms - were found to be stable. All testing phases were successful with both combinations of client-server configurations, transmitting data through a smartphone server to a PC client, and through a smartphone client to a PC server.

With this working environment, a C# implementation was developed within Unity using its .NET socket class[15], achieving the same data retrieval results as with Python. Considering the robustness required in later development of the project, further error handling functionality was included within this C# version, particularly regarding the loss of established connections and invalid data formats in the case of streaming interruptions. Later, these client-server connections were tested through an APK file built and installed onto the headset itself, and through the same testing phases conducted in the previous Python implementation, wireless client-server connections between the smartphone and headset were proven to be both functional and accurate in their purpose.

[15]https://learn.microsoft.com/en-us/dotnet/api/system.net.sockets.socket?view=net-6.0

4.4.2 Game functionality

Next, the development of game-related functionality included a series of sequential and dependent steps, categorised into controller input, enemy behaviour, a user health system and interface functionality, as well as various testing procedures completed throughout development. Each of these stages built upon and refined the functionality produced in previous iterations, collectively forming a complete and self-contained game.

4.4.2.1 Controller input

To manage input devices of the headset, a class managing the identification of connected controllers and subsequent controller interactions was created. Within the script's `Awake` function, called when the application is launched, any active controllers are assigned to a predefined dictionary variable containing a controller object for each hand, a headset controller that activates when no handheld controllers are available, as well as the positional anchors of each controller. Although the Oculus Go only comes with one controller – and so in the case of this project, only one may be active at any time, therefore setting the remaining objects to null – providing adaptable controller options allows the application to update to changes in users' hand dominance settings, and further provides pointer and selection interactions anchored to the centre of the headset view if controller connections are lost. Accordingly, scriptable events are also defined in `Awake`, invoked when controller connections are found or lost in order to manage changes in controller functionality if connection issues were to occur.

Various controller management functions are defined and called on connection changes, checking for new available controllers and updating the main source of input. With access to an active controller, button interactions are managed through `UnityAction` event objects, subscribed to by another script containing pointer functionality that defines when button press functions may activate, as well as the resulting behaviour of such actions.

Primarily, the pointer script performs continuous raycast traces from the active controllers' anchor positions, in the direction of their forward-facing orientation. Raycast visualisations are also presented through an inspector-assigned `LineRenderer`, allowing users to aim more accurately by mapping physical controller interactions to corresponding virtual visualisations. Regarding button press events, the subscribed `UnityAction` objects defined in the controller manager script trigger functions defining such button behaviours, which in this case, access the object that the controller orientation is pointing to through raycast hit detections, subsequently calling the `Pressed` function contained within the selected object. In this sense, all objects that may be interacted with must have an attached script including a public `Pressed` function, which defines the behaviour of that particular object when pressed. If a button is pressed while raycast traces do not detect an object – specifically, when the controller is not pointing at anything – the function returns without action. Unity's layer tools were additionally incorporated into this implementation, in which the raycast trace only identifies objects under the 'Interactable' layer, created specifically for controller interactions.

As well as orientational visualisations, optical reticule graphics are further managed by a separate dedicated script, changing the appearance of the virtual pointer's edge depending on the state of the raycast and whether it detects an interactable object. These visualisations are managed through additional `UnityAction` objects defined by the pointer script, which are subscribed to within the reticule script and therefore enable its graphics to be interchanged within the event fired on raycast state changes. As such, the reticule end of the pointer may allow users to recognise an interactable object through dynamic visual cues.

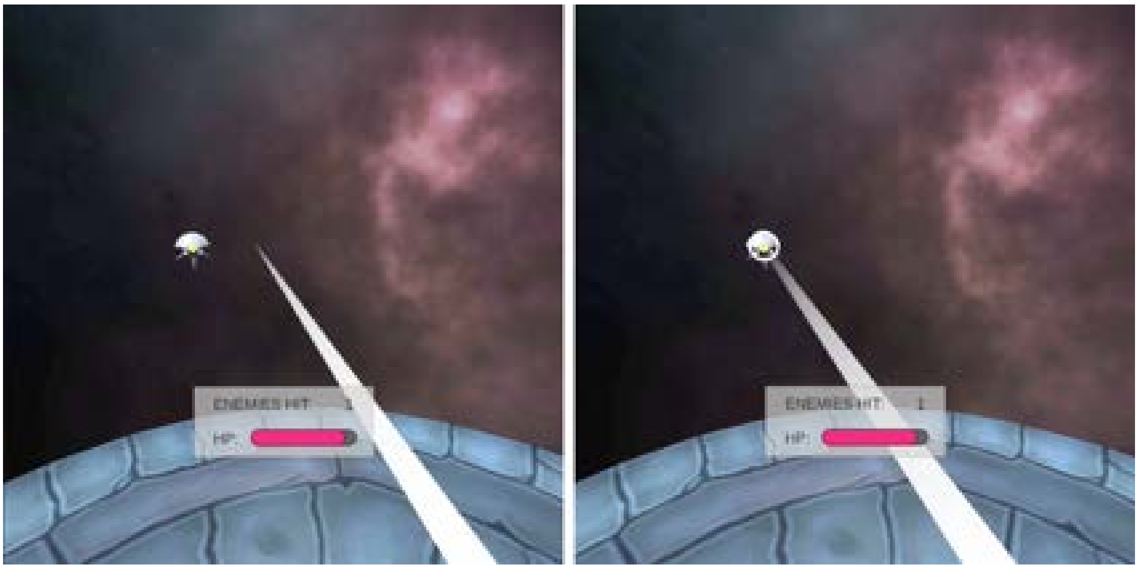

Figure 4.1: Screenshot of cursor pointer functionality, with its default pointer (left) and hover reticule (right) visualisations.

With this minimal functionality, only functional testing on the accuracy and performance of pointer visualisations and respective controller button interactions was required, employing temporary interactable objects with colour-changing properties emerging from button presses. These quick tests were built to the headset given the Oculus Go's deprecation and consequent lack of emulator resources, however they were successful in their operation and ensured that controller functionality was functioning as expected. In this sense, pointer visualisations were found to accurately correspond to physical controller movements, with clear reticule changes to indicate interactivity when hovering over objects, only for those under the 'Interactable' layer. The colour-changing properties of these temporary objects were additionally functional on controller button presses, indicating the successful implementation of all controller interactions.

4.4.2.2 Enemy behaviour

With the template functionality of controller interactions, the implementation of enemy objects with interactable properties was subsequently achievable. Through the Unity Asset Store, drone-like spaceship models with included missile weapons were downloaded and imported into the project[16], scaled and adjusted for a virtual reality environment. Serialising these modified enemies and missiles into dedicated prefab objects allowed easy instantiation within scenes and when scripting, attached with a `MeshCollider` for accurate collision detection and further assigned an 'Enemy' tag for efficient identification of these objects when activated in a scene.

Figure 4.2: Screenshot of the modified enemy prefab in the editor.

Spawning behaviours were first created, defining restriction bounds within a rough 180° arc around the user between 1.5 and three metres away from their starting position to ensure a comfortable but practical distance.

[16]https://assetstore.unity.com/packages/3d/vehicles/space/alien-ships-pack-131137

Through this script, a `Spawn` function included randomisation of a 3D vector within these specified bounds, containing an additional check for overlapping enemies. Explicitly, if any collisions are found between an existing enemy collider and a defined radius around the randomised 3D point, the function recursively creates another 3D vector and performs these checks again. Providing no collisions occur, an instance of the enemy prefab assigned to the script through the inspector is instantiated at the established vector position, and an integer storing the number of active enemies is incremented. This number of active enemies is verified against an integer denoting the maximum number of enemies allowed in the environment before performing the remaining procedure of this `Spawn` function, returning without action if this number is larger than or equal to the maximum value.

```
private void Spawn() {
  if(enemyNumber >= maxEnemies) return;

  spawnPosition = RandomPosition(); //generates random 3D vector within bounds

  if(!CheckCollision(spawnPosition, enemyRadius)) {
    GameObject e = Instantiate(enemy, spawnPosition, Quaternion.Inverse(Quaternion.
        identity));
    e.GetComponent<Interactable>().spawnScript = gameObject.GetComponent<EnemySpawn
        >();
    e.GetComponent<EnemyShoot>().shoot = shoot;
  } else {
    Spawn();
    return;
  }
  IncrementEnemies(1);
}
```

Listing 4.2: Function used to spawn enemies.

The `Spawn` function is called on a timer every few seconds according to a predefined timer variable, which updates based on the current number of enemies active. In this sense, enemies take longer to spawn when many are already active, and accordingly appear more rapidly when fewer have spawned. Such behaviour aims to increase the state of flow and immersion for users by maintaining an accurate difficulty level between individuals and their abilities – if users are slow at shooting and many enemies resultantly appear, then a slower spawn rate better suits their playing speed and mitigates increasing difficulty. Likewise, if users are fast and able to shoot many enemies at a quicker rate, then spawn rates are faster to match their pace and the reduced difficulty of handling fewer enemies at one time.

By attaching a script managing enemy shooting behaviours to the defined enemy prefab, missile obstacles are created with the intention of adding gameplay substance, as well as significance regarding simulated hypervigilance threats. Accessing the transform element of each instantiated enemy object, the `Update` function called once every frame includes a rotation mechanism that keeps enemies facing towards the user at all times, accessing the predefined Oculus Integration camera component that moves in virtual space along with the physical headset, therefore corresponding to user movement. Called every few seconds according to another defined timer value, a `Shoot` function instantiates missiles inside the enemy object, utilising Unity physics to add forward-facing force – namely, towards the user since enemies rotate to face the camera component during every frame – to the bullet's `RigidBody` component at a defined movement speed. Given that public variables cannot be automatically assigned in the inspector while the game is running, the script's `Awake` function loads the missile prefab from its local path, allowing one-time access for repeated instantiation.

While a collider had already been attached to the missile prefab, another `BoxCollider` was subsequently added as a child of the Oculus camera component, allowing the detection of collisions for future damage functionality. Configuring missile colliders as triggers, events may be programmed to react only when missiles overlap with the user collider, without the physics effects of rebounding collision behaviours. Within the enemy shooting script, missiles may either be destroyed when active for three seconds in the case that they have missed the user collider, or alternatively, are destroyed through a script attached to the user collider when collisions are detected.

Finally, an interactable script was attached to enemy prefabs in quick implementation of a simple shooting mechanic using the previously defined controller input template. Setting the enemy prefab layer to 'Interactable' and incorporating a public `Pressed` function within this attached script allowed enemies to be interacted with, being identifiable by the virtual pointer raycast as well as defining enemy behaviours in response to press actions. In this case, the spawn script is first accessed in order to reduce its stored number of active enemies, and then the enemy object instance is destroyed in 0.1 seconds.

To generate a basic click effect, similar to when a user interface button is pressed, the enemy object's material is set to null before the destroy function is called, leaving its mesh coloured with Unity's default textureless pink for 0.1 seconds before being destroyed. This click effect is useful in providing user feedback, supporting a visual response indicating that the enemy has been pressed. While another material or custom shader may have been applied, removing its previously assigned material was a quick method of applying such an effect, as opposed to creating a new shader script or material texture resource.

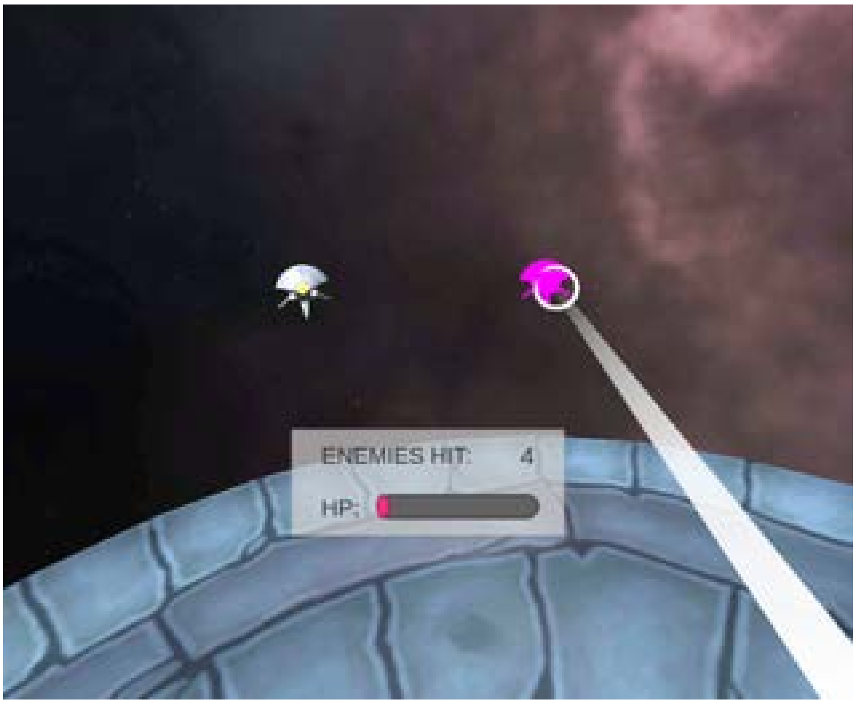

Figure 4.3: Screenshot of an enemy's removed textures when pressed through controller buttons.

At each implementation stage, testing was primarily carried out within Unity given that only controller interactions required testing through the headset. Debug logs and printed messages indicated the application's state regarding the values of various variables within each script, such as the number of enemies currently active, shooting speeds and intervals for each enemy, as well as in the detection of collisions, to ensure the expected behaviour was occurring at each point of interaction. Boundary value analysis was also performed in the number of active enemies given that the implementation restricts this value, and although values outside the specified range still permit the expected behaviour such that no errors or faults occur, functional testing ensures that the instantiation of enemies outside this range, including both positive and negative values, is not possible at any point throughout application use.

While automated unit tests were not implemented, these debug messages acted as a manual form of unit testing, alongside subsequent integration tests confirming that all implemented functionality operates together as required. The addition of controller interactions was tested last, building the application to the headset and employing end-to-end tests incorporating all present features, as well as methodical regression testing to ensure that previous controller functionality is not adversely affected by new features. As such, all enemy behaviour was found to function as expected, both in the system state that was observable throughout black box testing of debug messages at each stage of interaction, and through the practical employment of functional testing, utilising incorporated functionality.

4.4.2.3 Damage and health system

Given that colliders and collision detection mechanisms had already been implemented, tested and were functioning correctly, incorporating damage and health mechanics mainly required editing the existing collision detection script attached to the user collider.

An integer variable denoting the current health status of the user is defined within this script, initially set to 100 at the start of the game. Asserting the game is always started with 100 units of health, the function managing collision hits – originally only printing debug messages for testing – was then updated with reductions in this health value for every missile collision with the user collider, only while the current health value is larger than zero. For every hit, health is reduced by 5 units.

As evident in existing figures, quick and simple implementation of a user health bar to visualise these reductions in health included the creation of a UI `Slider` object with a removed handle graphic, allowing its fill status to represent the percentage of remaining health. By attaching the slider to this script within the inspector and subsequently accessing its fill percentage value, the slider can be continuously updated to reflect changes in user health by setting its fill status to the script's current health value, performed at each collision.

Through previous testing stages using the headset application, it was apparent that, while functionality was working correctly, enemy missile collisions could easily go unnoticed by users, particularly if getting shot from behind. To provide a better visualisation and awareness of damage taken, as well as highlighting the existence of enemies that were off-screen or behind the user, a transparent image with black faded edges was downloaded and assigned to the texture of a UI `Panel` component, scaled to the size of the headset's camera view. With inspector-assigned access to this border visualisation, an `IEnumerator` function to enable the panel for 0.3 seconds and subsequently disable it again was called within the user collider script at every missile collision, creating a damage effect in which collisions and resulting health reductions were highlighted for increased awareness.

Figure 4.4: Screenshot of border damage effects (right) compared to the default state (left).

Temporarily, the application was closed using Unity's `Application.Quit` function when health reached zero, ensuring that events could be triggered by complete loss of health and therefore establishing a template for zero-health behaviour. All such damage-related functionality was tested efficiently given the previously implemented template, confirming that the new changes are compatible with previous operations through integration testing on all application paths and interactions.

4.4.2.4 Menu and interface functionality

To finish the basic game mechanics of the application, a menu canvas acted as a mode separated from gameplay, facilitating transitions between gameplay and both start-up and game over functionality. The canvas itself included various UI `Panel` and `Text` components, attached to the Oculus camera such that the menu remained fixed in the user's field of view. As such, employing a canvas object rather than a separate Unity scene vastly improved the speed of transition, given that it is pre-loaded on start-up and does not require system transitions.

Figure 4.5: Screenshot of the menu appearing before and after gameplay states.

A script managing the activation and deactivation of separated menu and gameplay components dealt with the transition between these two states. Through references to each of these required components, a toggle function taking a single Boolean parameter activated either the menu or gameplay-related components according to the given parameter, such as the script spawning enemies and the canvas displaying current health, while disabling the opposing components. All active enemies are also destroyed on menu activation by searching for objects with the 'Enemy' tag, ensuring that no elements of gameplay continue when the game is over and the application state has changed.

```
public void ToggleMenu(bool enable) {
  menuCanvas.enabled = enable;
  gameCanvas.enabled = !enable;
  cameraCollider.enabled = !enable;
  enemySpawn.SetActive(!enable);

  if(enable) {
    GameObject[] enemies = GameObject.FindGameObjectsWithTag("Enemy");
    foreach(GameObject e in enemies) Destroy(e);
  }
}
```

Listing 4.3: Function used toggle menu and gameplay functionality.

Menu activation and subsequent gameplay deactivation is triggered both on application start-up and when the user's health value reaches zero, while menu deactivation is triggered through a controller button press while the menu is active. All gameplay-based reset functionality such as health restoration and default spawn timers had been moved to their respective scripts' `OnEnabled` function as a result, called every time these gameplay-related objects are enabled through menu deactivation and subsequently ensuring any variables changed during gameplay are reverted back to their default state.

Through deployment to the headset device, functional testing focussed on the accuracy of transitions between the menu and gameplay states of the application, first ensuring that no controller interactions interfered with those disabling the menu, then asserting that reductions in health resulted in a transition to the menu state once this health value reached zero. Specifically, such methods involved a form of state transition testing – systematically following every outcome corresponding to state transitions and events – performed to confirm that no further conditions, actions or events external to those intended could trigger unwanted state transitions, and that the required conditions of zero-health and menu-enabled button presses cause the correct state transitions to occur. Overall, successful testing found that menu and gameplay state functionality performs as expected.

4.4.2.5 Final testing and aesthetic adjustments

Final adjustments to the system included the use of skybox textures[17] and a floor platform model[18] – both of which were downloaded from the Unity Asset Store – to finalise the virtual environment in a cosmetic sense, as well as small modifications regarding spawn timings and instantiation zones. An off-screen target indicator was also implemented in a working PC environment during testing, however with conflicts between Unity's default camera component and the precise setup of the Oculus Integration's virtual reality camera component, this feature could not be successfully implemented in a virtual reality environment within the remaining time.

Functional and end-to-end testing was performed on repeated use of the completed application for various durations, particularly employing specific and unorthodox sequences of inputs such as repeated or incorrect button presses and controller targets, with the intention of locating potential bugs and errors during gameplay or state transitions. However, through both positive and negative path testing, no oversights or inconsistencies could be found, and so given that every instance of unit and integration testing throughout each stage of development proved reliable and functional according to the predefined requirements, the development phase relating to implementation of all underlying game mechanics was completed effectively.

4.4.3 Sensor data user study

With access to a functioning game as well as the ability to read and process real-time smartphone sensor data, the final step of development required the analysis of user behaviours during gameplay, utilising this sensor data in order to influence the virtual environment through changes in the game's responsive state. However, incorporating meaningful and user-centric techniques utilising sensor data regarding its reflection of deep breathing and meditation-like behaviours was necessary to ensure an appropriate implementation, purposeful in its representation of the underlying concepts employed.

[17] https://assetstore.unity.com/packages/2d/textures-materials/sky/starfield-skybox-92717
[18] https://assetstore.unity.com/packages/3d/environments/dungeons/floor-segment-20330

To investigate suitable methods of sensor data processing, a small user study was carried out before the final development phase, in which six participants used the application while carrying a previously set up smartphone device in their pocket, streaming real-time sensor data alongside active gameplay which was stored for evaluation and testing. Specifically, gameplay behaviours were matched with written notes of their corresponding sensor timestamps, linked to graphs after data storage and processing to visually determine what sensor data may correlate with the desired behaviours. Users were recruited from a lab in which selection criteria was minimal, only requiring an adequate level of sight and mobility, along with the dexterous use of one hand. While the primary intention of the study was to indicate this association between sensors and user behaviour, it also acted as a form of end-to-end testing with real users, with the opportunity to receive feedback about game-related functionality before executing the final development sprint.

Briefly, participants were asked to play a full round the game one or more times depending on their ability, preference or level of interest, for up to a few minutes. While observing the reactions of individuals during gameplay, each participant was encouraged to undertake deep breathing and meditation exercises when becoming visibly overwhelmed or energetic, in which timestamps denoting the start and end times of these changed user states were noted to ensure they could be identified in later analysis of the data. Given this flexible study procedure, the data gathered between participants differs in terms of accumulated timeframes and rates of slowed user states, however high consistency was not required providing that all participants expressed both default and meditative behaviours, with hand-labelled sensor data denoting the timestamps of these behaviours.

The initial Python script for client-server connections between a PC and Android smartphone was used throughout the study, modified to store streamed sensor data for each participant in a CSV file. Inertial sensors were emphasised in the identification of behaviour given the intended focus on user movement, namely including the device's in-built accelerometer, gyroscope and gravity sensors.

In the appendix, graphs of the gathered data display each of the three axes pertaining to every sensor, presented as a time-series line graph throughout the duration of the study.

Explicitly, the X-axis denotes consistent units of time in which packets of sensor data were transmitted, while the Y-axis relates to the absolute values of sensor readings. In presentation, these graphs are further grouped vertically by user, supporting the ability to infer correlations between each sensor, as well as the individual axis values within sensor readings, in relation to user behaviour.

By highlighting the areas of slowed user movement, noted by observation and subsequent timestamps during the studies, it is clear that these behaviours can be easily differentiated from typical gameplay states through analysis of inertial sensor data, even while the smartphone device is utilised from the user's pocket.

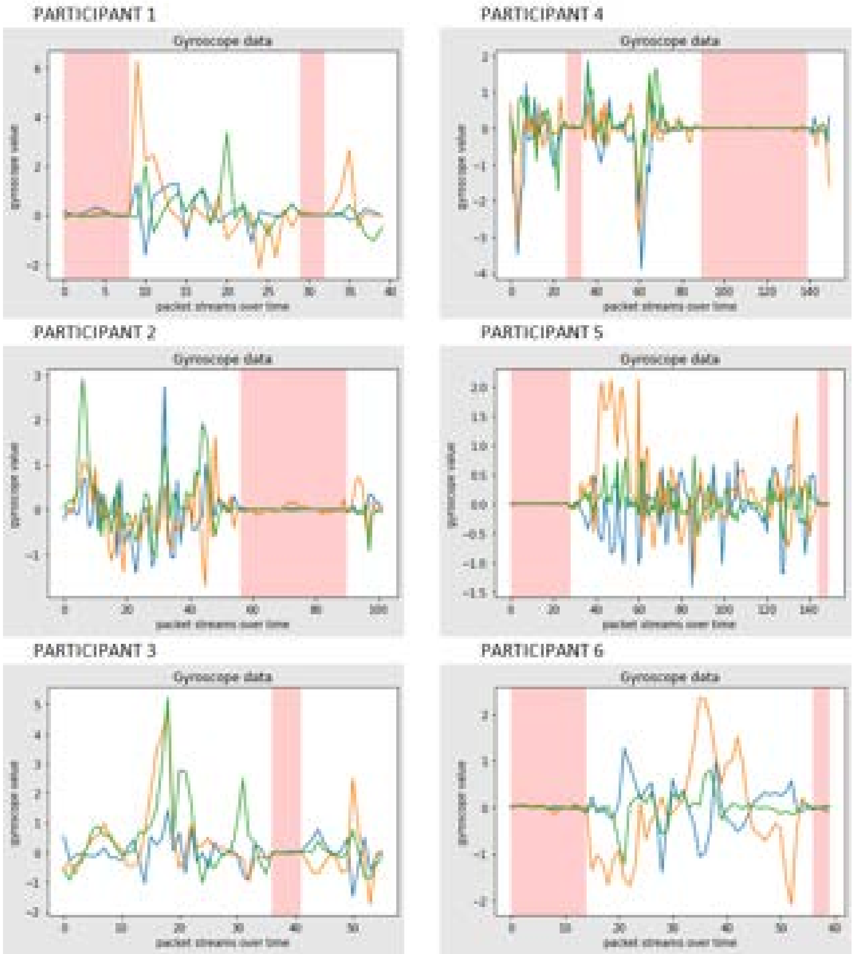

Figure 4.6: Graphed gyroscope data highlighted during slowed movement, for every participant.

Although such behaviours can be identified through accelerometer and gravity sensor data, roughly correlating within sensor axes on a vertically shifted Y-axis value, the gyroscope sensor appears to provide a more distinct and consistent reading of meditative behaviours, given the high contrast between default and slowed gameplay states. Through further analysis of this data, all three gyroscope axes appear to be within the range of -0.15 to 0.3 during slowed user states, which holds consistently for all participants in the study. As a result, the gyroscope sensor was determined to provide the most accurate and appropriate data for the identification and classification of behavioural states, where a consistent range of -0.15 to 0.3 may be used to distinguish such meditative conditions from regular gameplay movement.

Regarding the software testing purpose of the study, the application was found to run as expected with no errors or inaccuracies, stable across multiple consecutive games without any issues. Two participants independently provided constructive feedback for the next stage of development, where firstly, the use of audio was suggested in order to increase immersion and a sense of perceived presence, additionally beneficial in minimising external distractions and heightening concentration within the virtual environment [169–173]. Given that immersion and presence are key requirements and objectives of the project, this feedback was particularly valuable in the integration of concepts discussed within evaluation of the literature. The second comment concerned the size of the user collider, proposing it be made smaller because of difficulties in successfully dodging enemy missiles. Both forms of feedback were considered in the final stage of development, implemented within the predefined sprint timeframe alongside sensor-influenced functionality.

4.4.4 Sensor influence and improvements

Development during the final sprint involved both the incorporation of technical feedback received by participants, iterating and improving upon previous functionality in terms of performance and user experience, as well as the implementation of personal sensing according to the gathered gyroscope data, in which new features were added. Each of these aspects were completed in succession, within the originally defined timeframe.

4.4.4.1 User study feedback

In response to received feedback, three audio files were downloaded from the Unity Asset Store representing user damage, enemy damage, and enemy shooting sounds[19,20]. Along with an `AudioListener` attached to the Oculus Integration camera, `AudioSource` components were further attached to the user collider and enemy spawn script objects to contain accessible scripting references to each of these sounds. As such, the user collider script contains the user damage audio file, utilising the attached `AudioSource` object in order to play this sound when collisions are detected. Two `AudioSource` components were attached to the enemy spawn script given that it contains functionality managing reduction of the number of active enemies – in which the enemy damage sound is played within the public function called on controller button press interactions with enemies – as well as functionality involving the instantiation of enemy prefabs, allowing the shooting `AudioSource` component to be retrieved by each of these enemies at runtime. With direct access to the `AudioSource` component, the script managing enemy shooting behaviours, attached to every created enemy, is able to play this sound within the `Shoot` function that creates and adds directional force to missiles.

Feedback regarding the user collider was straightforward to implement, simply reducing its size parameters in three dimensions within the Unity inspector. Interface graphics such as the menu and health bar were additionally made smaller with a more visible position according to the virtual reality camera view, and through both functional and regression testing on practical application use, all adjustments and feedback-related additions were found to correctly function and improve the quality of gameplay experience. Such testing was performed quickly given the small number of adjustments, with similar techniques to those used in previous development stages.

4.4.4.2 Sensor data processing and implementation

In order to minimise interference with existing functionality, the main application scene was duplicated to allow reversion to a correctly functioning state in case of errors or incompatibility caused by sensor data implementation changes. Within this new scene, a temporary script was first created to produce continuous artificial data in the format

[19] https://assetstore.unity.com/packages/audio/sound-fx/retro-noisy-explosion-sound-pack-lite-69305
[20] https://assetstore.unity.com/packages/audio/sound-fx/shooting-sound-177096

of a smartphone's gyroscope data, building a sufficient testing environment without the requirement of client-server setups for the headset and smartphone devices. Data processing was then implemented through a `ChangeState` function, defining the range of -0.15 to 0.3 sensor value thresholds established during the user study. This allowed the identification of a user's slowed movement corresponding with gyroscope values falling within this boundary, including evaluation of whether this state has been sustained for over 0.5 seconds. In this sense, tracking sustained levels of slowed movement for a small period of time intends to ensure that the action is intentional, rather than fluctuating the activation of response to user behaviour, while also initiating action in a quick and responsive manner. When gyroscope values are no longer within the defined threshold, the game state reverts back to default.

Two `ChangeDifficulty` functions had been incorporated into the scripts managing enemy spawning and shooting, each taking parameters related to their respective stored data and updating values such as spawn rate, shooting rate and missile speed according to the given parameters. A reference to the spawn script was stored within the script managing sensor data, calling its public `ChangeDifficulty` function when a change in state is identified. When the state is slowed, larger parameters are sent to this function to increase the timers between spawning behaviours, whereas the default parameters are passed again when the user state is normal, reverting the game back to its usual faster pace. Similar behaviours were implemented with the `ChangeDifficulty` function for shooting rate and missile speed, however given that runtime game objects cannot be easily accessed or stored in prefabs, each spawned enemy accesses the sensor data script at runtime in order to track changes in user states, internally calling its private `ChangeDifficulty` function according to these identified changes.

To implement visuals indicating a physical change in state, a screen-size UI `Panel` component with reduced opacity was added to the canvas, additionally attached to the sensor data script in the inspector for activation access. Within state changes, this overlay effect is enabled during an identified slower state, and disabled during the default state. Through this visualisation, users may receive feedback regarding their sensor-indicated state, ensuring such behaviours correlate with their intended actions.

Figure 4.7: Screenshot of the overlay visualisation that appears during slowed states.

After state transition testing through artificial sensor data, the previously developed C# implementation of client-server sockets was incorporated, simply establishing the socket connection in substitution of the function creating artificial data and receiving real-time smartphone data as a result. Through further testing, sensor-influenced functionality was found to operate as expected, with a sufficient speed and quality of data streaming that allows accurate transitioning between game states. In this sense, systematic black box testing ensured that streamed data, as well as its corresponding processing methods regarding range evaluations and sustained behaviour, was accurate not only in its speed and consistency, demonstrated through debug logs and print statements in the form of manual unit tests indicating sensor values and system states, but also in the resulting system response, evident through functional testing on application use.

Similar to the previous data transmission testing methods conducted, endurance testing on the whole system and its response to streamed data was successful in its consistency and accurate representation of physical movement. However, given the required robustness of this application version, a form of recovery testing, primarily targeting the error handling functionality implemented in relation to the overall application performance, was additionally carried out by manually disconnecting the smartphone server and monitoring system responses accordingly. Error handling was found to seamlessly handle such occurrences, continuing application processes without the influence of smartphone sensor functionality. Although more robust recovery methods such as reconnection attempts or user-presented options were not implemented, simply ensuring the system does not crash or produce unrecoverable errors is sufficient for the small-scale nature of the project, especially given the demonstrated robustness and stability of smartphone data streaming, which suggests that streaming interruptions or inconsistencies are unlikely.

Finally, all pre-existing functionality implemented before this final sprint is confirmed in its compatibility with new sensor-related functionality through both integration and regression testing by monitoring application states, such as enemy spawn and shooting rates influenced by streamed sensor data, as well as through state transition testing on all menu, default gameplay and slowed gameplay states in combination, therefore completing all aspects of development for employment within user studies regarding the specific aims and specifications of the project outcomes.

4.4.5 Revision of traditional intervention methods

While the application primarily intends to demonstrate prototype concepts of virtual reality and sensor technology within an intervention context, its design also aimed to incorporate approaches with the potential to improve upon the shortcomings of traditional loneliness interventions. As stated in the project motivations, many researchers stress the inadequacies of existing socialisation strategies [45, 53, 57, 80–83], particularly due to their inaccessibility and ineffective nature [57]. The core rationale behind this typical lack of success has been attributed to (1) the focus on objective social isolation rather than subjective loneliness itself, (2) neglect regarding the diverse multidimensionality present in loneliness as a chronic condition, and (3) the lack of personalised approaches that target individual needs and contexts [45, 53]. As such, the novel and unique functionality available through virtual reality augmented by personal sensing data has been proposed as a means of revising such oversights.

4.4.5.1 Subjective social isolation

Regarding loneliness, research identifies that interventions addressing maladaptive social cognition are much more effective than those reliant on increasing social interaction and developing social skills [45, 50, 53, 87]. As such, changing, confronting and overcoming the internal thoughts, behaviours and emotions that are detrimental to the condition of subjective social isolation builds a more permanent solution to dealing with loneliness in daily life, as well as improving its underlying psychological concerns [45, 50, 53, 55].

To implement these concepts, the application simulates a hypervigilance environment in which users may receive repeated exposure to learn and become familiar with strategies to overcome these detrimental behaviours. Specifically, the application encourages a meditative state when overwhelming hypervigilance behaviours occur through the demonstration of beneficial outcomes – explicitly, slowing the game speed and making its experience more manageable – when employing this desired reaction, therefore incorporating the ideas of cognitive behavioural therapy by addressing individuals' internal behaviours. In this sense, functionality focuses on enforcing strategies that intend to equip users with trained practical experience by utilising these virtual interactions, which may be applicable in real-life hypervigilance scenarios. Through the immersive experience of virtual reality, overtaking the senses of sight and hearing along with a correlation between physical actions and those replicated in the virtual environment, the application also employs a sense of perceived presence that has been beneficial to the success of many cognitive behavioural therapy technologies in past studies [20–25, 40, 162, 164], improving the quality of practical experience and realistic responses to the simulated environment [40, 41], which has further been proven to increase treatment response in a cognitive behavioural therapy context [19, 168, 172, 173].

4.4.5.2 Multidimensionality of loneliness

Given the multidimensionality of loneliness in relation to its diverse range of cognitive, emotional and behavioural variables [50, 53, 55, 88], researchers suggest that determining the causal relationships between loneliness and these characteristic features is necessary in order to provide better treatment and intervention strategies [50, 55]. While the application itself does not necessarily focus on the understanding of inherent correlations between such variables for the identification, assessment and treatment of loneliness, its real-time use of sensors demonstrates how such features might be built into a cognitive behavioural therapy environment, establishing methods in which inertial movement data can identify relevant behaviours through the analysis of user-tracking data. The implementation design additionally highlights the potential processing of resultant user reactions within a virtual environment, such that causal relationships between presented stimuli, external behaviours and internal psychological response may be measured and investigated in application to loneliness, or leveraged to reflect the virtual reality experience.

At this initial stage, no data is stored about users during application use, and as such, the developed application provides an introductory template in which additional sensors or further data processing, particularly through machine learning techniques on a large quantity of data, may track loneliness-related behaviours over time in order to identify symptoms, assess progress and predict the future developments of an individual's condition or state, inherently taking the psychological, biological and behavioural characteristics of loneliness into account through personal sensing technology. With access to a chronic loneliness userbase, these attributes may be utilised in machine learning model training to better understand the condition of loneliness in a multidimensional manner [7, 10, 12–14]. Automation of objective data collection is another advantage of such systems [10, 11, 17], receiving empirical reactions and behavioural data from a purposefully employed environment, as opposed to the manual and subjective self-assessment questionnaires currently used [10, 15].

4.4.5.3 Personalising treatment

Personalisation is the final component of successful intervention strategies said to maximise the efficiency and effectiveness of treatment by directing strategies towards individuals' personal needs and contexts [53, 55, 56]. Despite this significance, it has been found that traditional loneliness interventions often employ a universal, generalised approach for all patients irrespective of the variation and divergence experienced between individuals, therefore disregarding their unique psychological state and circumstances [53, 55, 56].

The concepts of such personalised treatment are implemented through an adaptive virtual reality simulation that reacts to user behaviours according to the analysis of real-time sensor data. In this sense, ease of management regarding the gamified hypervigilance environment is increased through better self-regulation of demanding, high-alert situations, therefore promoting employment of these behaviours to those who react more negatively by enforcing a situation in which behavioural management through meditative strategies is actively beneficial. Therefore, the induced experience differs between users and their inertial behavioural response, optimising difficulty and enforcement of behaviour according to interactions on an individual level, subsequently demonstrating the ability to address the individual needs of users across various forms of loneliness through environments that invoke the most appropriate experience regarding detected reactions to presented stimuli.

Chapter 5

User study

Utilising the final developed system, participants were subsequently gathered in operation of a primary user study, aiming to evaluate the application in its purposeful inclusion of personal sensing in combination with virtual reality technology. Various planning and management processes were conducted in preparation, and qualitative results are presented in relation to the emerging themes categorised by predetermined hypotheses. In this sense, aspects pertaining to the overarching aims and requirements are explored, aiding the evaluation of such technology in application to loneliness and mental health.

5.1 Study goals

As seen through a review of literature and related work, studies utilising virtual reality, personal sensing or a combination of both technologies are typically successful in various healthcare and mental health domains, and in this sense, the integration of these employed concepts within a loneliness context is hypothesised to produce comparably successful results. Given the introductory nature of the project, gathering qualitative data regarding users' experiences, opinions and learnings through use of the application is a main focus of the study, as well as evaluating the application itself in terms of both functional performance and perceived purpose, therefore assessing whether concepts highlighted in the literature are incorporated appropriately and as intended.

Through this user feedback, the study overall aims to evaluate whether the use of sensors and virtual reality would be suitable in a human-centred application to loneliness, through the example implementation of hypervigilance concepts. Explicitly, the fundamental hypotheses of the study are stated as follows.

HYPOTHESIS 1: ***Users understand how to use the application and can recognise its purpose through unguided use.***

Through minimal guidance regarding the application's purpose and functionality, the study aims to identify whether its meditative cognitive behavioural therapy intention, alongside the corresponding response to behavioural changes, is apparent to participants through sufficient use and experience. As such, these results will establish the achievement of perceivably relevant integration of these concepts according to participant perspectives, in comparison to the intended behavioural outcomes as a result of application use. Assessing these perceptions through both verbal responses and observation of behaviour is important in order to examine whether the implementation of intended concepts effectively adheres to user values and understanding.

HYPOTHESIS 2: ***Users accept the employed application of virtual reality and sensors, and perceive them to be appropriate in their purpose.***

In terms of both functional performance and implementation design, appropriateness and impactful use of developed functionality within an intervention context should be evaluated, ensuring that details regarding the internal operation and methods employed are trusted and accepted by its users. Explicitly, such investigations include the suitability of game-based cognitive behavioural therapy, the virtual environment and its incorporated interactions, as well as the use of inertial sensors, subsequent behavioural identification and system response, all of which are assessed on participant judgement, interpretations and practical experience throughout the study. This analysis aims to determine whether users feel that design and implementation is meaningful according to the concepts the project is trying to represent, additionally testing functional performance such that these technologies and features are correctly functioning and resultantly beneficial in conjunction with one another, towards the application's intended purpose.

HYPOTHESIS 3: ***Users experience aspects of the literature that are successful in related works, such that their incorporation or demonstration is effective for user outcomes.***

Employing interview topics relating to concepts covered in the literature, particularly regarding the improvement of current loneliness interventions and respective rectification methods found in modern mental health innovations, associated participant experiences will be evaluated and compared throughout the study. Primarily aiming to establish prevalent findings consistent across all participants, such results may demonstrate the level of concept integration that has been achieved, as well as the evaluation of their effectiveness in application to such technologies. While expressed experiences compose these findings, behavioural observations during application use may contribute as well, exploring whether the integration of such concepts is beneficial to perceived outcomes, as well as user experience in general.

Through hypothesis outcomes alongside the analysis of relevant results, a preliminary conclusion regarding suitability of employed technology – incorporating the discussed factors such as performance, acceptance, perceived purpose, meaningful implementation and overarching study outcomes – will be reached with the intention of aiding analysis of the universal application of these solutions to loneliness interventions. Such conclusions will be utilised in comparison with the literature, related work and state-of-the-art in order to strengthen the validity and completeness of decisions.

5.2 Study design and procedure

In related works and similar areas of research, study procedures carried out to evaluate developed technology interventions are commonly performed through cooperation with participants diagnosed with the relevant condition in question, measuring reductions in symptoms [19, 21, 33, 177], a change in psychological state [11, 56, 178], or comparisons between groups of users over prolonged application of the system [11, 123–125, 141, 142, 145, 146, 148]. Regarding sensors specifically, many evaluations test the accuracy of sensor data and processing algorithms by comparing their resulting indications against participants' self-reported diagnostics [11, 101, 110–114].

Various limitations prevent the application of such procedures within this introductory project, particularly regarding time restrictions and user access. With the absence of a chronic loneliness userbase, psychological and behavioural effects that the developed system may have on loneliness and its related symptoms cannot be verified, and alongside the limited timeframe available, not only are longitudinal measurements over prolonged application use unachievable, but classifiable behavioural data for loneliness symptoms cannot be gathered through a user-targeted and long-term use of sensors. Ethical implications are also a concern in such contexts, particularly regarding the application of minimally-tested technology, potentially containing misleading therapeutic intent, for deployment with vulnerable users.

As a result, this study procedure instead focuses on the collection of qualitative data regarding the personal experiences and opinions of participants, evaluating whether the intended, expected or desired behaviours are caused as a result of application use, with the overarching measurement of suitability and acceptance regarding such technology in the given context. With the intention of analysing this human-centred insight into user interpretations, the procedure involves a one-to-one session with each participant in a quiet designated room lasting approximately 30 minutes in total, with the overall process split into three parts. Explicitly, these three parts include (1) a small demographic questionnaire to gather preliminary data, (2) practical use of the application while observing physical behaviours, and (3), a detailed interview covering predetermined topic areas in a semi-structured manner, aiming to gather the relevant data for accepting or rejecting the defined hypotheses. With no medical-specific target audience, participants were recruited locally with a selection process similar to that of the previous sensor study, explicitly including adequate levels of sight, hearing, mobility and the dexterous use of one hand, intending to gather as many participants as possible through no further restrictions. However, those who took part in the initial sensor data study were excluded given their prior experience with the application.

Within the first phase of the study, participants completed a pre-study questionnaire to the allow assessment of demographic data such as age and gender, along with important preliminary information including prior experience with mental health applications, trust regarding sensor-based data collection, and familiarity with virtual reality technology.

This test is primarily useful in defining common practice and general levels of experience, as well as establishing the overarching beliefs concerning such technology and whether these opinions change throughout the study.

Participants were then instructed to use the developed application during the second phase, equipping the virtual reality headset and smartphone device with minimal guidance regarding the system's purpose or functionality. For each participant, multiple playthroughs of the game were completed to allow for better familiarity with the controls and exploration of sensor functionality, where behaviours and changes over time were observed and noted for future analysis. Given the self-contained interaction process of this gamified application, detailed procedure plans and resources were not necessary during this phase of the study, enabling participants to use the application with freedom and independence.

Figure 5.1: Example photo of study setup.

On completion, participants were to report their experience and findings through a semi-structured interview, covering the overarching topics of perceived purpose, appropriateness of functionality, and aspects relating to the concepts prevalent in reviewed literature. While the employed structure and guideline questions are included within the appendix, some examples are as follows.

- What do you think was the application's purpose?
- Why and how do you think data was being used?
- Does sensor data influence the game in an appropriate way?
- Did your experience or behaviours change over time?
- Did you feel immersed in the game?
- Were you aware of any external distractions?
- Do you think this experience would be the same, or differ between individuals?

After reviewing initial thoughts about the application, its intended purpose and underlying concepts were conversationally discussed within the interview in order to gather more targeted responses regarding opinions and meaningfulness of implementation. Participant responses were noted manually, and utilising written comments gathered during both the interview and observation of application use, thematic analysis [216] is applied in the investigation of qualitative data to derive conclusions from overarching participant responses. In this way, categories of results analysed from each participant may be compared across the population in order to determine a more comprehensive conclusion.

5.3 Safety, ethics and security precautions

A number of safety precautions were taken during the study, as well as assertions regarding ethical and security concerns. Given that virtual reality obscures vision of the physical environment, the study procedure was performed in an open space permitting unrestricted movement, subsequently ensuring no obstructions were exposed, and as such, the study took place in a safe location that minimised the risk of injury or interference. Additionally, all participants were made aware of potential motion sickness caused by virtual reality, particularly when the headset device is not fitted correctly to the user [217]. As a result, extra caution was ensured when setting up the device, and participants were instructed to stop the study at any point in which such sickness may occur, as well as in the case of any other forms of physical or emotional detriment. Through these mitigations, no participants experienced physical interferences or motion sickness during the study, and expressed no manner of further harm.

Matters of bias, medical accuracy, machine learning concerns and study population had minimal influence given the preliminary nature of the developed application and study, and so ethical concerns were reduced to a minimum. In this sense, user opinions and experiences composed the primary focus of the study, such that no declarations of treatment efficacy or expected outcomes were proposed or intended. Similarly in terms of security, no data about users or their inertial state is stored by the application itself – only processed in real-time – additionally containing no use of personal, identifiable or sensitive information. Fundamentally, the initial questionnaire collecting demographic data was the sole inclusion of personal information within this study procedure, namely including participants' age range and gender as well as technology-based opinions, however this data is entirely anonymised and possesses no identifiable indications.

5.4 Demographics and preliminary data

An overview of the participant population can be portrayed through summarised preliminary data, gathered in the demographic questionnaire. Seven participants were recruited locally with the minimal selection criteria stated, in which users with prior experience of the application were not involved in this study. As such, all participants had no knowledge about the system and its potential or intended interactions, or regarding the context in which it may be used.

Equal numbers of participants were aged between 18 – 24 and 25 – 29, making up all but one participant, falling into the category of 30 – 35. Of these participants, just over half were male.

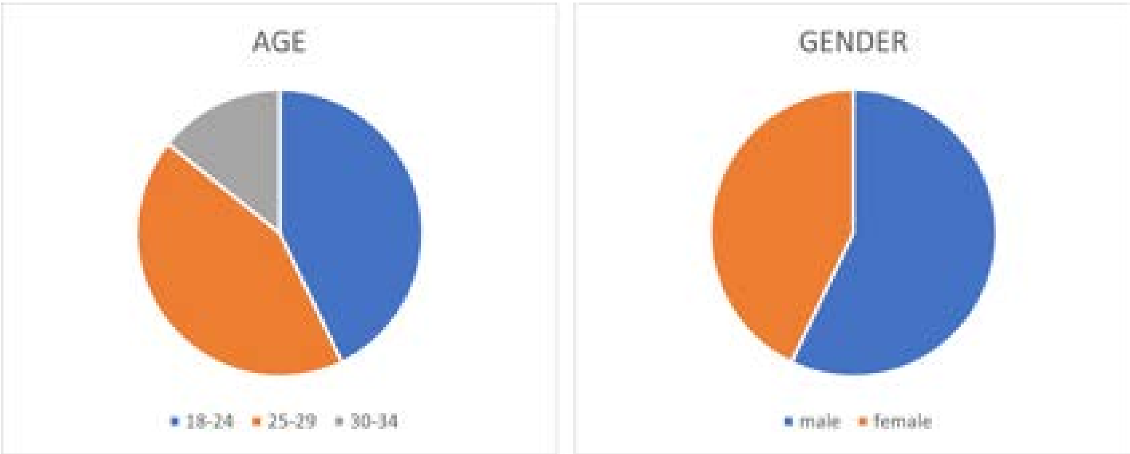

Figure 5.2: Summary of participants' demographic information, including age range (left) and gender (right).

Three of the seven participants had used or currently use technology applications for the management of mental health, two of which include the implementation of personal or sensor data. Specifically, one smartphone application observes and manages various biometric data calculations through smart watch sensors, providing information and visualisations of various physical implications such as sleep quality and activity levels. While the application itself is not designed with mental health intentions, the participant stated that they used it as such, tracking behavioural patterns over time in correlation to symptom characteristics and medication changes. The other participant's application, additionally utilised with a smartphone device, regards management and reminders for medical information, appointments and medication, primarily operating through user input data. Both participants felt these respective uses of data were appropriate in their purpose, stating that such methods contribute to the application's functionality and efficacy, as well as the user's resulting management of conditions. One participant additionally noted the optionality of such data uses, in that using data is permissible if users provide it by choice. While the number of participants utilising technology for mental health is slightly in the minority with three out of seven, especially concerning applications employing personal or sensor data in just two of these participants, results show that such practice is currently accessible and found beneficial in daily life.

Five participants, demonstrating a relatively large majority, indicated relative acceptance of behavioural data use, providing a score of three out of four for Likert scale responses.

Only two participants were not so comfortable with applications measuring behavioural data, one of whom being entirely against such functionality. Through comments relating to these responses, the participants most unaccepting of behavioural data tracking indicated distrust in the automated collection of data and the potential uses of such information, in which the participant most disapproving did not want any person or device to have access to self-related data. Other participants did not appear to have strong opinions, typically stating that the analysis of user behaviour is acceptable provided that it is beneficial in its purpose, and that utilised data is both secure and minimal according to the required information.

Regarding use of inertial data, participants were generally more accepting in Likert scale responses, with the majority giving three or the maximum of four, each stated by three participants. Given an explanation of inertial data, participants were typically more or equally comfortable compared to behavioural data in general, primarily as a result of its non-personal and anonymous nature. One participant was still against this use of data, consistent with their previous response relating to behavioural information, again through a distrust of any digital access.

Figure 5.3: Summary of participants' acceptance of behavioural and inertial data usage in applications, and level of experience with virtual reality.

Finally, many participants at four out of seven had minimal experience using virtual reality technology while still being somewhat familiar with its application, whereas one participant stated no prior experience with the technology at all. Despite this majority, one participant had adequate experience while another had a great level of experience, which provides a widespread range of abilities that facilitate usability testing for a variety of users. Those with minimal experience expressed an interest in such technology for leisure purposes despite the lack of previous opportunities, one in particular explaining no existing need for virtual reality use in general. The remaining participants with moderate and high levels of familiarity both owned a virtual reality headset, one belonging to a family member and one being a personal device, in which such experiences were considered entertaining and enjoyable, primarily utilised for gaming applications.

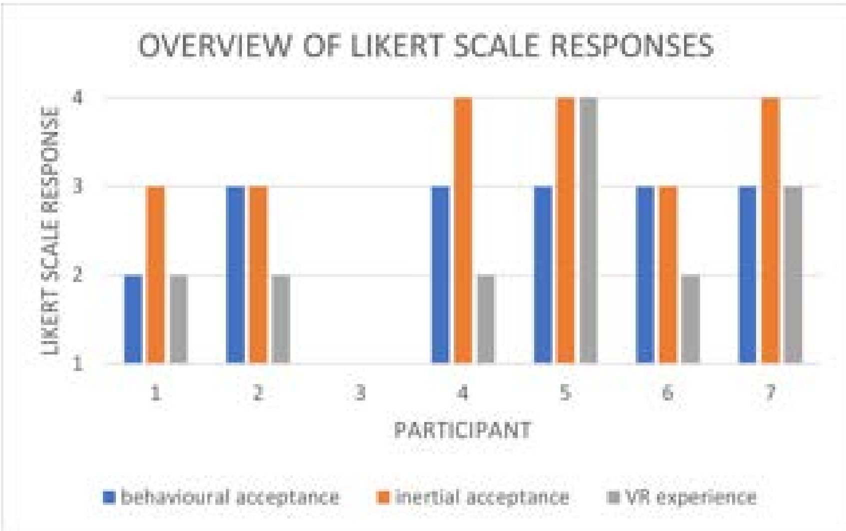

Figure 5.4: Within-participants grouping of Likert scale responses, from one to four.

Overall it appears that there are prominent commonalities within Likert scale responses, while also providing a reasonable level of variance. For instance, the majority of results indicate a moderate acceptance of behavioural data use within applications, with this trend increasing to equal parts accepting and very accepting for that of inertial data. The security and individualisation of data was a main factor of this perceived acceptance, along with the assertion that data is not used for unrelated purposes. Additionally, while participants with all levels of virtual reality experience are involved in the study, there is a high proportion of those with little experience, along with a desire to become more familiar with its applications. In this sense, all participants expressed interest in the technology, and particularly those with less experience were excited about opportunities to use virtual reality devices.

5.5 User study results

Through thematic analysis [216], themes in written notes during the observation and interview phases of the study have been deductively coded and categorised according the defined hypotheses, including following additions of inductive coding themes throughout this analysis process in order to refine segments of these topics further. While many of these categories related directly to the questions pertaining to them, various overlaps and subsidiaries are evident within participant responses, prompting this more rigorous form of coding data for qualitative analysis.

5.5.1 Recognisable purpose

The first set of categorised themes relate to the first hypothesis, aiming to evaluate whether participants were able to perceive the intended application of the system, both in its concept representation and in its overall purpose. During the second phase of the study, all participants discovered the sensor-influenced functionality of slowed gameplay through unprompted exploration of application use, in which most participants utilised this functionality alongside increased levels of perceived difficulty. As intended, the feature was often used as an opportunity to pause and take a noticeable deep breath, whereas one participant appeared to take advantage of the slowed difficulty state in order to safely scan and observe the virtual situation. However, such methods were not always successful, typically triggering a transition to the application's default state through increased physical movement. In this sense, continued behaviours of hypervigilance do not seem to be not endorsed by the implementation processing inertial movement, forcing an entirely meditative state in order to control the difficulty of the application.

When explicitly asked about functionality during the semi-structured interview, all participants understood the employed use of sensors in that behaviours arising from inertial data influenced the difficulty and state of the application. However, only three participants recognised the meditation-related intent of this feature, stating that having the ability to slow game speeds encouraged such behaviours and a resulting sense of recovery from stimulated over-awareness. Correspondingly, cognitive behavioural therapy techniques were also implicitly mentioned through recounted experiences of sensor functionality.

"It was helpful to recover my composure when lots of [enemies] were appearing."

"When it let me slow everything down, it kind of persuaded me to change my reactions . . . I was more aware of my breathing."

Other participants perceived this purpose as a method of personalised difficulty management, or a feature mapping physical attributes to in-game speed through correlation of user motion. While such interpretations are comparable to what is mechanically implemented, they do not define the purpose of its implementation.

Regarding the virtual environment and its associated interactions, no participants explicitly identified hypervigilance as a purpose or design intention, however various related cues were indicated by every participant. As suggested in the previously stated quotes, all referred to the need for high levels of awareness, highlighting the hypervigilance concepts induced. In response to questions regarding user experiences in relation to the virtual game environment, participants often used phrases such as 'high alert', 'awareness' or 'looking around'.

"I did feel like I was always on high alert, but it was more fun than stressful because it was a game. I felt like I was in the zone."

"I was looking around everywhere . . . you have to be really aware of everything."

In this sense, vigilance-related themes incorporating these responses indicate the awareness of such concepts, despite their lack of association with the application's intended purpose. However, alongside observational analysis during the phase of application use, an implicit understanding of hypervigilance concepts as an underlying design reflection was evident across the duration of the study, given that all participants are not only aware of its deliberate influence, but also used the application conforming to its intended purpose - explicitly, undertaking an increased state of alertness and managing meditative behavioural reactions as a result. Fundamentally, a subconscious perception of awareness and hypervigilance appear to be evident among participants despite no explicit identification of such concepts relating to overall purpose, therefore portraying a more inadvertent association than that of explicitly acknowledged sensor data.

To summarise, the intended functionality of inertial sensor data was most recognisable through application use, and while the purpose of such functionality was identifiable across nearly half of the participant population without guidance and explanation, other participants did not independently perceive this connection. Similarly, the implementation of hypervigilance-related concepts was noticed by all participants, being a particularly prominent topic within this stage of the interview, although were not necessarily associated with the purpose and outcomes of application use, despite evidence of implicit understanding. However, the overarching cognitive behavioural therapy elements were clearly identified by some and indirectly suggested by others, both within interview responses and through behavioural observations while using the application. Few participants explicitly noted behaviour change and self-awareness outcomes as a result of functionality intentions, however this purpose has been evidently recognisable throughout the study, especially with the identifiable deep breathing and meditative behaviours employed alongside increases in perceived difficulty as a result. As such, the hypothesis stating that the application's purpose is recognisable through unguided exploration may be cautiously accepted, given the overarching understanding and adoption of these underlying themes throughout the first phase of the study, therefore demonstrating an association with the fundamental values and recognition of participants.

5.5.2 Appropriateness of functionality

Themes extracted in analysis of the second hypothesis target perceived appropriateness of design and implementation according to functional performance and the application's intended underlying purpose. Regarding sensor data, it has been established that all participants understood its functional operation and influence on game-related states, though subsequently, all participants believed that the application of such data was both relevant and suitable within the specific context, especially given its purposeful functionality in contribution to the overall purpose. Six mentioned the accuracy of behavioural analysis especially, in which the application was consistent and precise when identifying deliberate changes of state in physical movement, responding accordingly by activating a slower difficulty. As such, the general opinion across the participant population was that the particular sensors and processing methods used were correctly able to identify these intended behaviours, and were therefore appropriate in their purpose.

"It's like the minimal data required to read your movements. It was pretty accurate."

"It actually impacts the game and means something to do with the way it works."

Ease of use was another advantage identified by two participants, additionally relating to the appropriateness of sensors used. In this sense, both the unobtrusive nature of smartphone devices and the wireless transmission of their sensor data were deemed beneficial in application.

"Using the phone for sensors doesn't get in the way or anything, I always have my phone in my pocket so it's just the same as normal."

"You don't have to use wires and attachments like you do with other things . . . like those finger clips or ECGs."

Finally, appropriateness regarding trust of sensor monitoring techniques was incorporated into the interview given the initial examination of participant opinions within the demographic questionnaire. Alongside purposeful use that contributes to meaningful functionality, four participants also noted the non-personal and anonymous form of data that influenced their perceived appropriateness of sensor functionality, typically expressing value in that the application only utilises the essential data required to perform these corresponding behaviours.

"I like the fact that it uses anonymous data."

"You don't need to use personal or identifiable data, which probably makes people more willing to use it."

Through these responses, it appears as though the initially more cautious acceptance of behavioural tracking in mental health applications was improved through the example employed within the application, however the participants who mentioned the significance of such anonymity were also those originally most accepting of inertial data processing, possibly demonstrating a positive correlation between data usage acceptance and awareness regarding non-personal methods of using data.

Generally, the processing accuracy, meaningful functionality, ease of use and minimal, anonymised sensor data were all themes that contributed to perceptions of high suitability and appropriateness of sensors in their design and implementation, therefore demonstrating that participants found sensor-based functionality appropriate in its purpose across a range of defining factors. Accuracy and meaningful functionality were the most commonly identified reasons influencing perceived appropriateness, however over half of these participants were also influenced by the anonymous and non-personal use of data that was both minimal and relevant in its application. These results correspond to those established in the initial Likert scale questionnaire, such that the same themes of acceptance factors regarding inertial and behavioural data utilisation were found after using the application as well. Particularly, it is clear that the application's use of sensor data adheres to user values that are most influential towards acceptance and compliance.

Various comments additionally considered the appropriateness of the virtual environment and its incorporated interactions through discussion of hypervigilance concepts, particularly in the experience stimulated through extended application use. As previously mentioned, participants often referred to the induced state as a heightened alertness and awareness, though indicated that the experience was not necessarily stressful in the sense of causing panic or anxiety, only in that the constant stimulation required consistent levels of concentration. Surprisingly, no participants considered the potential ethical concerns of inducing hypervigilance through a potentially stressful situation, and instead recognised the experience as enjoyable when asked directly. In this sense, the employment of functionality that is existing in many virtual reality games, solely used as a reflection of hypervigilance rather than actively imposing it, may be successful in minimising harmful reactions.

"Any game could be thought of as stressful, but it's part of the experience. It's supposed to be entertaining, and if you don't like it, you don't have to play."

"I could just slow everything down when it was going too fast ... it made me change the way I react."

Responses regarding this experience often appear to indicate a state of flow, an optimal state of consciousness in which difficulty corresponds to ability, consequently inducing a fully immersed sense of focus [218, 219]. In this way, appropriateness of the design and implementation of hypervigilance concepts were typically thought to be suitable in their intended representation and purpose, given that the virtual environment successfully elicits the intended state of awareness and attention. Six of the seven participants conclusively understood the correlation between game functionality and hypervigilance concepts and consequently believed that such representation, by design and implementation, is appropriate both towards the overall purpose of the application, and in its functional performance given that no inaccuracies or errors were encountered at any point during the study and therefore did not interrupt such levels of concentration. However, one participant did not clearly indicate this understanding, although conversely agreed with the overarching opinion such that the virtual environment and its reactions did cause the desired experience and state of awareness, regardless of the lack of association demonstrated.

Overall, participants generally felt that the integration of virtual reality and sensor data was effective in combination, with three participants in particular referring to the efficacy of such functionality within a cyclic manner. Specifically, these responses attributed to the virtual environment's ability to induce the desired state, the resulting influence in encouraging meditative behaviours, and the reliance upon sensors to measure changes in this state in order to iteratively influence the virtual environment and consequently the user's state again. As such, participant perspectives and practical experience of the application demonstrate that the choice of technology is deemed appropriate, both exclusively and in integration with the complete system and its overarching functionality.

"It's good how everything works together ... even though [the headset is] separate to the phone's sensors ... it seems like they're all a part of the same thing."

"Being in VR causes the behaviour that's picked up on by the sensors, which changes what happens in VR when it senses the changes . . . shows that they both have their own purpose, but also work together . . . towards the same thing."

No participants particularly commented on the Oculus Go headset itself, however there were equally no faults or technical difficulties throughout the duration of these studies, suggesting its use was instinctive, intuitive, and resultantly subconscious. Relating to the choice of employed hardware, minimal obtrusiveness was a main decision factor of both smartphone and headset use, improving the intuitive ease of technology utilisation such that it is inconspicuous for users, and does not cause any discomfort.

Considering the overarching acceptance and expressed suitability of design and implementation regarding both virtual reality and sensor technology, including a range of diverse factors encompassing themes within functional performance and overall intended purpose, the hypothesis of perceived appropriateness can be decisively accepted through the consensus demonstrated across the general participant population. As such, participants were found to trust and respect the underlying implementation constructs, and found value in their application and objectives.

5.5.3 Incorporation of literature

Relating to the third hypothesis, themes were categorised according to each of the concepts discussed in review of the literature, aiming to evaluate their relevance in application to the developed system. In this sense, responses correlating with the three main criticisms of current loneliness interventions and their amendments have been extracted intrinsically – namely, methods of addressing internal cognition, incorporating the multidimensionality of causal variables, and personalising treatment according to individuals' needs – as well as successful methods employed in related works with the potential to integrate these amendment strategies, such as personal sensor-adaptive treatment, cognitive behavioural therapy, virtual immersion and exposure, as well as an induced sense of presence.

5.5.3.1 Effectiveness of cognitive behavioural therapy

Firstly, cognitive behavioural therapy is a procedure known to address the internal, maladaptive functioning of intrinsic behaviour, to a much larger extent than traditional socialisation methods. The influence of the application's cognitive behavioural therapy impact on perceived purpose has been demonstrated within evaluation of the first hypothesis, in which participants utilised the relevant functionality alongside an increase in perceived difficulty, distinctly in order to manage breathing and induce a temporary meditation state. Additional observations during application use also indicate, in general, a more purposeful employment of such states over time, particularly finding that games lasted longer through better management of reactions with increasing experience of meditative functionality. As a result, participants appeared to develop a calmer default state over the duration of application use, even as difficulty remained the same, therefore implying an improvement in self-regulated behaviour.

As mentioned, three participants explicitly indicated resulting behavioural change or awareness, through personal values pertaining to the cognitive behavioural therapy concepts intended. These established findings validate the successful demonstration of such concepts and that users are able to learn from the experience, particularly over extended use, conclusively for nearly half of these participants and implicitly amongst others. When directly asked about learnt experiences or impactful results of application use in later stages of the interview, the same three who previously identified behavioural change as a purpose of the application again mentioned the acquired ability to control reactions through the employed meditative behaviours, however three additional participants identified such capabilities in potential applications of the system. Through these further prompts, six of the seven participants overall expressed experience of this behavioural influence.

"I guess it trains you to calm down when there's lots going on."

"It could be used in mental health settings, to show people how slowing down and breathing properly can be helpful if you're stressed."

"I definitely learnt to recover . . . it helps to stop and breathe for a second."

One participant even noted that they would employ these strategies in everyday scenarios, and in future developments, would like to use the application over consistent, prolonged periods of time. Although no other participants stated this belief in relation to themselves, five mentioned such applications and their benefit for other users, particularly those suffering with mental health issues. The six participants all agreed that regular use of the application would more productively and permanently encourage behavioural change and self-regulatory management of meditative techniques, however the empirical significance of longitudinal use is unclear through one small user study. Despite this uncertainty, behavioural awareness increased among three – and implicitly all – participants through a single practical application, demonstrating its potential in long-term adjustments of intrinsic behaviour.

Various aspects covered in the literature have been thought to improve the quality of cognitive behavioural therapy, particularly regarding the application of virtual reality. Briefly, the concept of exposure as a subset of cognitive behavioural therapy has been identified as a successful use of virtual reality in several mental health intervention contexts, and was covered within the semi-structured interview to a small extent. Two participants independently commented on the potential of repeated exposure to situations inducing a high state of alertness, and when explicitly discussed, every participant supported the concept as a means of training internal reactions, even though one expressed that the application itself does not induce sufficient levels of controlled stress or anxiety in order to generate a large enough impact for effective exposure therapy in isolation.

"I think exposure therapy is supposed to push people to confront fears . . . it has to be quite intense to cause a big enough reaction, probably a lot more intense than this game is."

"If you get more experience with something you can't deal with, you'd get used to it . . . and overcome it."

Similarly, immersion and presence are additional factors proven to enhance the effects of cognitive behavioural training, found to be a key contributor towards virtual reality's unique capabilities in the successful application to such methods. At various points in the interview, all participants indicated a sense of immersion and virtual presence, which through the theories of presence previously defined, may be categorised into distinct aspects of spatial presence, involvement and realness. To summarise, spatial presence denotes the sense of physically being within the virtual space, involvement relates to a state of focus regarding virtual stimulus – particularly in dismissal of competing external factors – and realness represents the level to which the virtual environment and its interactivity coincides with expectations of real life.

Participant responses often suggested a sense of spatial presence, which typically appeared to increase over time. In particular, comments mentioned a lack of awareness regarding physical presence, five of which stating that they forgot about the physical environment in immersion with virtual stimuli. In this sense, virtual presence surpassed and outweighed physical presence.

"I forgot where I was while I was playing."

"I forgot about everything else, I was completely immersed in the game. I didn't even realise we were doing the study until I took the [headset] off and I remembered."

Comparably, as established throughout the interview and aforementioned analysis, participants evidently developed high levels of focus in relation to the involvement component of presence, apparent through indicated states of alertness and awareness. A distinct contributing factor to immersion and the resulting sense of presence, explicitly mentioned by three participants, was the incorporation of shooting interactions and the need to physically react to the environment. Such interactivity was found to create a more active response, in which passive experiences would not have contributed to equivalent levels of immersion. The influence of physical interaction on increased states of alertness were also apparent among the wider participant population during the observation phase of the study, with the level of focus increasing through more involved and committed interaction.

"Having something to do [physically] definitely made me more focussed."

In combination with spatial presence in which participants noted a lack of awareness regarding the physical environment, the implementation of interaction demonstrates that competing external factors of attention were naturally dismissed through use of the application, therefore conforming to a focus on virtual stimuli and consequently, a heightened state of presence as evidenced in the literature.

Regarding perceived realness, participants did believe in the given environment and reacted as such when immersed within application use, despite the unrealistic appearance of virtual elements. For instance, three participants in particular were visibly affected by virtual stimuli while using the application, flinching on enemy missile collisions as if the impact was real. All participants adopted the interaction techniques and behaviours pertaining to the virtual environment in a natural manner, further displaying correlation between the environment, its interactivity, and the expectations and resulting behaviours of real-life interactions. Four participants clearly indicated a sense of perceived realness within interview responses, stating that reactions are instinctive through subconscious processing.

"In the back of my mind I know it's not real, but when you're in the moment, your body reacts as though it is."

"I didn't actually think that it was or wasn't real, I just kind of accepted it without thinking anything."

As such, the three components of presence were evident throughout both observation and participant responses, especially apparent after reflection through discussion of these concepts. All participants additionally indicated the benefit of such presence through application use, inducing a higher level of concentration and impact regarding inherent behavioural change, as well as more naturalistic reactions.

"Being so immersed in the game probably made it more effective for changing my reactions."

"I definitely reacted more naturally, so it's probably more applicable to real life . . . [presence] also made it more fun."

5.5.3.2 Personalisation of user experience

In the concepts improving traditional loneliness interventions, personalisation is another vital strategy encouraged by experts throughout the literature in this domain. As seen in related works, the use of personal sensing to individualise the identification and treatment of conditions, as well as in adapting and influencing the functionality of virtual reality and similar technology applications, has been a successful technique of such personalisation solutions. Through observation of participants, the experience and interactions regarding application use appeared to be vastly divergent between individuals, influenced by inertial behavioural response captured through real-time sensor data. In this sense, ease of management regarding users' perceived difficulty significantly adapts through various levels of self-regulation, evident in these reactional observations.

Five participants independently identified such personalised and adaptive experiences, expressing value in the ability to tailor exposure and subsequently invoke the appropriate response according to detected user behaviour. One participant especially noted the ability to address individual needs through this personalisation, in which various forms of behaviour may be evaluated and accounted for.

"For people who become too stressed and active, it'll force them to slow down and recover . . . it depends on how you react."

"Everyone would experience it a bit differently."

As previously identified, participants often indicate an experience of flow throughout application use, such that the level of perceived difficulty is optimal according to user ability. Even though the methods and responses through which participants approached the application were distinctly varied, this optimal level of difficulty appears to hold among the participant population, indicated to be around the right level by every participant, despite their contrasting experiences. Accordingly, this association may imply an accurate implementation of response to user behaviour, in which levels of self-regulation are managed and analysed appropriately in the variation of consequential experiences - by adapting to unique user behaviour, the most suitable system response is generated on an individual level. As a result, the inclusive results regarding personalisation and sensor-based adaptivity demonstrate potential in addressing individual needs and contexts among various users and their diverse behavioural contexts.

5.5.3.3 Demonstration and potential of multidimensionality

The final aspect of the literature includes incorporation of multidimensionality. Although inherent correlations between causal variables are not assessed in treatment of cognition and behaviour, the application's use of real-time sensor data demonstrates the potential of such functionality through a one-dimensional example, identifying meditative behaviours following induced hypervigilance through the analysis of processed data.

As such, the interview incorporated discussions surrounding the application as an introductory concept in multidimensionality, in which the diverse structure of causal and correlating variables may be conducted through additional sensors or sophisticated processing techniques. While participants agreed that the current implementation was not necessarily multidimensional, four claimed that there is vast potential in such methods in their utilisation, specifically mentioning features like longitudinal behavioural tracking and the management of treatment progress.

"It could track [sensor data] over time to show patterns and trends."

"If someone used it over a few months, it would be useful to show their progress . . . including different types of sensors would make it more accurate."

All participants believed that the diverse structure of variable correlations would be identifiable through the use of additional sensors or data processing techniques that extract a wider range of behaviours. In particular, biological information such as heart rate or blood pressure was most commonly mentioned, in which six participants indicated their potential effectiveness in application to behavioural measurement.

"I think heart rate would be a good one. You could sense if someone's panicking or something."

"Blood pressure can be related to stress and anxiety."

Significantly, one participant expressed personal experiences regarding self-assessment measures of mental illness, and believed that the automation of data collection in order to empirically understand, manage and review various conditions would be another relevant advantage of causal analysis.

"It's hard to quantify how you feel and how to express it . . . [self-assessment] takes up a lot of time. If I could play these games and have them work everything out for me, it would be fantastic."

As such, through understanding of the difficulties faced through the inherent multidimensionality of behaviour and cognition, this participant expressed that the automatic analysis and assessment of conditions, leveraging a diverse range of sensing types and their corresponding processing techniques, would be an improvement compared to the existing methods that they are currently familiar with. While no other participants suggested the potential of such automation, results indicate the relevance of familiarity in assessing contextual needs.

5.5.3.4 Significance of literature incorporation

In summary, elements of cognitive behavioural therapy were successfully identified among participants and were thought to be beneficial in their implementation. Presence in particular was not only one of the most evident factors regarding the efficacy of cognitive behavioural therapy, but was also noted to positively impact outcomes relating to the dynamic awareness and resulting meditative purpose of the application. Regarding personalisation, such concepts were additionally apparent during application use, especially in terms of the ways in which participants experienced and interacted with the virtual environment. Incorporation of these adaptive experiences was widely perceived to be valuable in adapting presented stimuli in order to invoke the most appropriate response, based on individuals' various reactions and psychological contexts. Finally, all found that the application demonstrated an introduction of multidimensionality concepts, and resultantly, participants saw benefit in potential applications utilising a range of sensing modalities to better understand the causal relationships between conditional variables, and therefore adapt to user responses.

In essence, incorporation of aspects relating to those reviewed in the literature appears to be positively successful though the overall participant consensus, both within interview discussions and through observation. Valuable outcomes are demonstrated by incorporating the methods found to be successful when employed within related works, which consequently shows that such technology has high potential in its intervention efficacy, especially regarding user experiences and engagement. As a result, this third hypothesis regarding effective incorporation and user experience of literature concepts, including demonstration of their valuable impact, may be accepted through the overarching literature-related themes extracted comprehensively.

Chapter 6

Discussion

In general, the user study conducted alongside use of the developed system aimed to evaluate two main sets of findings. Firstly, the suitability of personal sensing in combination with virtual reality technology is explored within a loneliness intervention context, utilising primary results in participants' experiences and opinions regarding functional performance, perceived purpose and appropriateness of incorporated functionality, in conjunction with the concepts and findings found across relevant literature in this domain. Secondly, an indication of such technology's potential in improving upon the defined weaknesses of traditional loneliness interventions is assessed, particularly through the system's demonstrated incorporation of methods successful in studies and interventions employing similar technology innovations. These determined conclusions also include the contribution of literature concepts in relation to the overall value and effectiveness of the system, additionally important in its comparison with traditional intervention strategies.

6.1 Suitability of technology in loneliness treatment

Regarding the employed technology and its use within a loneliness context, user study results suggest high suitability and pertinence across various contributing factors. The implementation of gyroscope data and its corresponding processing methods were clearly perceivable and considered especially appropriate in the accuracy, meaningful functionality and minimal, anonymous use of data, conforming to user values of acceptance and commitment to its underlying purpose. Although sensor accuracy in the context of identification and management of conditions – the most common application of sensors found across healthcare literature – was not a focus of the project, other similarities with explored research can be found through the concepts of sensors discussed. For instance, sensors employed in smartphone devices are typically most effective in expressing the physical or external behaviours of users, in contrast to the internal bodily reactions or psychological models extracted from biomedical sensors and software sensing respectively [10, 12, 56, 149]. As such, smartphone gyroscope data employed within the application was highly effective throughout the study in its measurement of physical motion, utilised in a way that could accurately distinguish deep breathing and meditative responses from regular gameplay movement. This correlation supports the suitability of smartphone sensors in their ability to measure external behavioural factors, particularly in the example application of hypervigilance-related concepts. As a result, a non-functional requirement of the system, defined as a purposeful and practical use of sensors with a meaningful influence on the application, has been achieved through these results. While the causation between inertial data and the indicating factors of loneliness symptoms has not yet been explored, the system demonstrates a practical application in which such data may be used, given that the majority of existing loneliness interventions employing sensor data focus on software sensing [15, 57, 85, 110], along with a highly specialised biomedical application utilising brain network detection devices [56]. The identification of contrasting hypervigilance and meditative states provides an example of how inertial data may be used to extract symptoms and behaviour pertaining to loneliness, which may assist in the monitoring, treatment and diagnosis of the condition and its severity.

Alongside demonstration of sensor suitability, the virtual environment was also a successful factor indicated within study outcomes. In this sense, alertness and flow were effectively induced within an enjoyable and engaging method of cognitive behavioural therapy, utilising gamified interactions to encourage the meditative behaviours analysed through sensor data processing. As found in the literature, virtual reality is unique in its immersive capabilities that are valuable in application to cognitive behavioural therapy [19, 32–39], contributing towards the effectiveness of long-term confrontation of negative internal functioning, particularly by adapting the embedded, intrinsic behaviours of users [19, 20, 38, 39, 42–44]. Primary results demonstrate an effective reflection of the intended hypervigilance state, as well as the personal identification of this encouragement regarding behavioural change – explicitly shown to improve behavioural awareness and incentivise techniques that are effective in managing hypervigilance symptoms – therefore correlating with literature successful in employing these concepts. While this conforms to the non-functional requirements of adequately representing cognitive behavioural therapy concepts within an adaptive virtual reality environment, it also demonstrates the technology's suitability in application to loneliness, given the importance of targeting maladaptive cognition in the treatment and management of chronic loneliness conditions [45, 50, 53, 55, 87].

Similarly, the non-functional requirement of endorsing an enjoyable user experience, primarily in order to encourage positive attitudes towards treatment and to contribute towards successful behavioural change, has been covered through results indicating positive participant opinions and impressions of such methods, prominent across the population and particularly through expressions of desired continual use. Gamification is evidently a key contributing aspect for such motivation, seen to be a popular study subject of behavioural management within sensor-adaptive virtual reality research through the employment of Nevermind, in which various aspects of gameplay are altered in response to sensor data measuring stress and fear [193]. Primary study results correspondingly express an enjoyable experience, which not only encouraged positive attitudes towards such methods of treatment, but also contributed towards identifiable behavioural change and increased self-awareness. These results are especially significant given the typical lack of motivation regarding existing loneliness interventions, often emphasised to be inaccessible due to factors such as social stigma [45, 57, 86].

Within literature of this domain, presence is the most established factor of effectiveness in application to virtual reality systems for cognitive behavioural therapy [20–25]. Consistent with the success found in related works employing factors of presence, this concept in particular was found to be a prominent influence in participant perceptions and outcomes throughout the conducted study, contributing towards the induced state of flow and alertness, as well as the overarching cognitive behavioural therapy purpose itself. Specifically, the combined impact of spatial presence and interaction produced a higher level of engagement through immersion and active involvement, subsequently enabling easier dismission of competing external factors and distractions in the physical environment. Perceived realness was additionally deemed beneficial through its presented association between the virtual environment, its interactivity, and the expectations and behaviours pertaining to real life, therefore inducing natural and instinctive responses to virtual stimuli to an extent comparable with physical exposure. While these results prove the influence of each factor in relation to immersion and presence, they also demonstrate the value of presence in the outcomes of cognitive behavioural therapy concepts, given that such levels of presence induced a higher level of concentration and impact regarding inherent behavioural change. As a result, primary findings are consistent with those explored across the relevant literature, and subsequently, the non-functional requirement regarding presence induced by the developed system is evidently achieved. Through these factors of presence, virtual reality and its unique capabilities within this context supports the technology's suitability in application to loneliness, and especially proves its valuable potential in the ability to induce naturalistic responses better than that of traditional laboratory environments [20, 40, 41], seen to be important in the success of cognitive behavioural therapy [19, 21, 24, 176].

Overall, the combination of sensors and virtual reality were effective in their coordination, successfully creating an immersive and adaptive cognitive behavioural therapy experience that can identify user reactions and subsequently encourage behavioural change at an individual level. Functional performance and appropriateness of this combination were valued throughout personal perspectives, observed behaviour and expressed outcomes during the study, in which practical experience of the developed system demonstrated the effectiveness of employed technology in its intended purpose, both exclusively and in their integration. Therefore, the overarching results and subsequent acceptance of hypotheses pertaining to effectiveness according to user experiences establishes the suitability and appropriateness of such technology in its demonstrated application to loneliness. Given that hypervigilance is such a detrimental aspect of loneliness as a chronic condition [45], especially contributing towards morbidity and premature mortality through its alteration of psychological processes and cognitive functioning [14, 45, 53, 56, 57, 60, 73, 77–79], the evidently high capabilities and demonstrated potential of such treatment using virtual reality and sensor technology is a significant advancement in addressing these damaging symptoms.

6.2 Improvement of traditional loneliness interventions

By design aiming to address the limitations of traditional interventions most commonly applied in loneliness treatment, achievement of the second aim has been accomplished through the capabilities demonstrated in utilisation of the employed technology. Firstly, confrontation of maladaptive social cognition has been widely present throughout primary results on the developed application, where as discussed, the combined functionality of personal sensing and virtual reality technology has evidently contributed towards behavioural awareness and subsequent adaptation outcomes. In contrast, the typical intervention strategies focussing on socialisation are frequently considered ineffective within loneliness literature, given that such approaches do not address the cognitive biases that characterise loneliness as a chronic condition [45, 50, 53, 55, 87]. As a result, interventions directed towards intrinsic improvement of the thoughts, behaviours and emotions that underpin loneliness symptoms are said to provide more permanent and effective treatment [45, 50, 53, 87]. Primary study results evidence the implementation of adaptive and immersive cognitive behavioural therapy through virtual reality and sensor technology, enabling treatment that targets internal psychological functioning with the intention of changing maladaptive cognition. In particular, results indicated an identified awareness and encouragement of meditative behavioural techniques found to be effective against hypervigilance symptoms, therefore demonstrating the effectiveness of such methods according to participant impressions and experiences. As such, the potential of this technology establishes an improved alternative to the traditional methods emphasising increased social opportunities and developing social skills, instead addressing the causal factors behind loneliness and its fundamental determinants.

Results also indicate the promising potential of personalisation through the introductory application within a loneliness context, in which the experience and interaction strategies employed between individuals were evidently diverse from observation of use. Current loneliness interventions have been criticised in their minimal capabilities regarding personalisation [53, 55, 56], fundamentally unsuitable due to the divergent experiences of loneliness across different circumstances and backgrounds [14, 45, 53, 56, 73]. As such, perceived value in the developed system and its ability to tailor exposure and subsequently invoke an appropriate response, particularly for individuals' unique needs and contexts concerning their reactions to virtually presented stimuli, was a key finding from the study regarding participant perspectives and experiences, showing that this technology has potential in addressing the levels of personalisation currently lacking from traditional loneliness interventions. Literature also suggests the importance of further research in the identification of prognostic digital biomarkers that represent loneliness constructs, stated to improve the personalisation of treatment through understanding of individuals' internal structures [53, 56]. Even through the preliminary application employed, this system supports such concepts of personalisation through the identification and differentiation of both hypervigilance and meditative states, along with the potential to analyse individuals' characteristics through this behavioural management in the case that such data were to be digitally stored. In this sense, methods of personalisation required according to the divergent nature of loneliness have been demonstrated through the collaboration of virtual reality environments that are influenced by real-time sensor data, measuring user interactions and tailoring treatment appropriately.

Finally, the capabilities of multidimensionality have been preliminarily approved through employment of the developed application as a demonstration of suitability within an intervention context. Particularly regarding inertial measures of data such as those used within the project, research concerning the psychological and behavioural multidimensionality of loneliness is currently lacking in existing literature, and the inherent, causal relationships between loneliness and its characteristic features are relatively ambiguous as a result. As seen through biomedical studies in loneliness research, whole-brain RSFC has been successful in predicting loneliness through network connectivity of the brain, accordingly identifying the prefrontal, limbic and temporal systems as determining factors [56]. Despite this introductory research of biological loneliness structures, trackable physical or external behaviours of loneliness are currently unclear, and so the inertial factors of a user's meditational or hypervigilance states have been demonstrated in their measurement, analysis and subsequent system response, instead aiming to distinguish the intended reactions that are encouraged within users' self-management techniques, moreso than the behaviours pertaining to loneliness itself. Study results find this implementation to be accurate in the detection of these states, expressing the ability to identify and extract such symptoms and behaviours in response to stimulated environments. This also determines the potential for further data processing in understanding the inherent correlations between these behaviours and the fundamental condition of loneliness, possible in future research through large volumes of sensor data gathered through an established loneliness userbase. As such, a significant discovery from the conducted study was the recognisable implementation and purpose of multidimensionality concepts through the application of sensor data and its resulting influence on users, in which the use of a diverse range of sensing modalities was often suggested in its implementation, correlating with recommendations in research regarding the robustness of sensor processing classifications [10, 95, 96]. These findings clearly demonstrate the potential of this technology in employing methods of multidimensionality through additional sensing modalities, particularly through the achievable application of machine learning techniques performed on real-time sensor data that have been successful in state-of-the-art sensor systems and the overarching literature in this domain [7, 10, 12–14].

Inclusively, each of the criticisms regarding traditional loneliness methods have been demonstrated in the improvement supported by virtual reality and sensor data in integration, through both implementation effectiveness and proven potential. This technology is evidently suitable in application to loneliness interventions, with vast capabilities in developing treatment efficacy and subsequently improving the standard of care for those suffering with loneliness.

Regarding real-world deployments, results show that the speculated application of the system, as defined in its design, is reflected in participant responses and experiences, specifically regarding the suitability of a future, more robust implementation in clinical cognitive behavioural therapy contexts, both within expert sessions and in the independent management of personal loneliness conditions. Such value is demonstrated through expressed outcomes in that behavioural awareness and improvements were evident across the participant population, particularly being a desired method of mental health treatment, however given the gamified nature of the application and the overarching entertainment influence that emerged as a result, it appears that even users who do not suffer from loneliness may also find benefit in such a system, and that more casual technology interventions could be additionally valuable in scenarios less formal than cognitive behavioural therapy sessions, such as for entertainment purposes alongside the primary intention of adapting detrimental behaviours.

Chapter 7

Summary and conclusion

The importance of addressing loneliness has been established through the motivations of the project, alongside the creation of effective solutions that are valuable in this purpose. Loneliness is commonly referred to as a discrepancy between desired and existing social relationships, predominantly regarding the quality of such connections [14, 45–54]. As discussed, the condition has been identified as a predecessor and cause for depression, anxiety and stress [45, 50, 57, 60–62], and the implicit hypervigilance resulting from loneliness further impacts psychological processes and functioning [45, 53, 63] which, in extreme cases, increases morbidity and triggers premature mortality through weakening of the immune system [14, 45, 53, 56, 57, 60, 73, 77–79].

Despite this significance, current treatment and intervention strategies have been criticised by loneliness experts [45, 53, 55–57, 80–85], driving the need for more effective innovations that can address the multidimensional variance between individuals' circumstances, such that intrinsic maladaptive cognition and behaviours are targeted and confronted. Through a review of healthcare innovation literature, the application of emerging technologies such as sensors and virtual reality hold high potential in the improvement of traditional loneliness interventions, particularly in the utilisation of such technologies in synergistic combination.

To support this development, three aims had been defined in the investigation of these concepts, firstly relating to the exploration of virtual reality and sensor technology in application to loneliness based on existing studies and innovations, secondly the development of a prototype application that may demonstrate the potential of such concepts through adherence with successful literature, and finally the evaluation of the developed system in conjunction with the discussed research, objectively evaluating the potential and suitability of such technology within a loneliness intervention context.

The first aim was satisfied through a comprehensive review of literature, related work and state-of-the-art solutions within healthcare domains, establishing high potential in both sensor data processing and virtual reality technology in their potential application to loneliness interventions, both in isolation and combined. Various methods and concepts throughout this review were valuable in the design aspect of such treatment, constructing the foundations of application development.

This subsequent development focussed on the integration of hypervigilance concepts given their detrimental significance on loneliness as a chronic condition, creating a self-contained virtual reality game utilising real-time smartphone sensor data in order to identify, process and adapt to user behaviour. All defined functional requirements were met solely through implementation of each relevant feature, as well as non-functional requirements relating to performance. While implementation and testing covered requirements FR1 through FR6 along with NFR5 and NFR6, later user study results also confirmed the attainment of non-functional requirements NFR1 through NFR4, particularly in the perceived purpose and appropriateness of features alongside the overall user experience. Close abidance to the methods successful in related work was employed, aiming to ensure an incorporation of effective treatment concepts that were additionally motivated by the limitations of traditional loneliness interventions.

Finally, a user study employing the developed system was conducted in compliance with the third aim, evaluating subjective experiences and opinions on the application through interviews and observation. The main findings of the study suggest that functionality is both accurate and appropriate according to its intended purpose, and that concepts discussed in research have been incorporated effectively and are impactful on the success of intended outcomes.

In this sense, all aims have been covered over the scope of the project, and through each stage, the application of virtual reality and sensor technology has proven beneficial in the context of loneliness treatment, not only in their success in the example application of hypervigilance concepts, but also in their ability to improve upon the weaknesses identified in current loneliness interventions. While the developed system is only an introductory demonstration of such ideas, the values expressed aim to encourage and inspire better intervention development for loneliness and its related mental health and wellbeing concerns, providing a template in which future work may be built upon to advance the research area further.

7.1 Contributions

One of the most significant achievements of the completed project is the successful development of an immersive, user-adaptive and gamified intervention strategy utilising sensor data and virtual reality technology, shown to be effective in its purpose through user study results. Particularly, these results demonstrate the ability to actively encourage meditative behaviours during hypervigilance environments alongside the accurate identification of user behaviour, subsequently adapting virtual stimuli in order to produce an appropriate personalisation of user experience. In this sense, the design and implementation of the system utilised technology and concepts successful in related work, and fully embodied literature in this domain to produce a solution that can be beneficial in application to loneliness, and further, to improve upon typical intervention limitations that are deemed ineffective. Through this system, many contributions lie in the demonstration of suitability regarding the technology employed, such that unique characteristics of presence, cognitive behavioural therapy, behavioural tracking and gamification are proved both valuable and achievable through the capabilities of real-time sensors within virtual reality, among many other concepts discussed. Gamification in particular is currently non-existent within the field of loneliness, and so the contribution of such methods is especially significant given the minimally motivational methods of treatment currently employed [57]. Contrasting loneliness intervention literature, primary results establish an engaging and enjoyable experience induced by the developed application, in which frequent use was desired.

In comparison to current loneliness interventions, the potential of virtual reality and sensor technology has evidently demonstrated the ability to improve upon the weaknesses identified by loneliness experts. A review of literature finds that virtual reality is particularly valuable in application to cognitive behavioural therapy, that personal sensing has the ability to account for the multidimensionality of loneliness through various data processing techniques, and that the combination of these technologies – utilising sensor data to adapt virtual reality experiences – provides the personalisation of treatment currently lacking in traditional intervention approaches. As such, user study results indicate the unique capabilities of this technology in improving the previously identified limitations, demonstrating effectiveness in addressing internal maladaptive behaviours, personalising such experiences according to the reactions and contexts of individuals, and establishing the potential to account for the causal relationships between the multidimensional factors of loneliness. While many academics discuss the inadequacies of current methods, few studies direct research towards solving such limitations, and so the developed application may contribute an introductory investigation of practical solutions to be employed within interventions.

Another contribution may be the proof of importance regarding the incorporated literature concepts. User study results significantly demonstrate the value of perceived presence in cognitive behavioural therapy outcomes, such that spatial presence and involvement contribute to increased attention, engagement and investment within the virtual environment, particularly through purposeful interaction and dismissal of external distractions, whereas perceived realness corresponds to the authenticity of reactions caused by virtual stimuli, induced by representative correlations between virtual interactions and those expected in corresponding physical scenarios. Another important finding involving presence asserts that the realistic appearance of virtual environments is not necessary in order to generate a sense of presence, given the abstract presentation of the virtual environment employed. Although the theory of such concepts has been highlighted in previous work, results gathered throughout the project not only evidence the effective implementation of presence, but also the conclusive value of these constructs given their beneficial impact on behavioural awareness and perceived self-management importance.

All such knowledge and intrinsic understanding is essential in maximising the efficacy of treatment, ensuring the design of future interventions can implement the demonstrated concepts, therefore adopting comparable successful findings in order to genuinely benefit those suffering with loneliness. While the contributions representing suitability in the employed technology, methods and application of literature are beneficial to the research area in demonstration of effective treatment and subsequent improvement of traditional interventions, the project primarily proposes an introductory investigation into the use of novel technology solutions in their potential value to loneliness. In this sense, the overarching contribution is the preliminary research conducted, establishing foundations on which future work may develop, and therefore aiming to encourage better progress and valuable research within loneliness treatment.

7.2 Limitations and future work

In continuation of the project, the essential aspects to develop further include the integration of multiple sensors in order to better understand the inherent correlations between loneliness and its causal factors, along with the collection of labelled data through longitudinal studies with a chronic loneliness userbase. The restricted implementation of multidimensionality may be the most significant limitation of the project, and so with additional time and resources, the incorporation of various sensors – including a range of psychological, biomedical and inertial data – and their impact on virtual cognitive behavioural therapy is hypothesised to develop the understanding of loneliness further, particularly given user study participant perspectives on the effectiveness of biomedical data in this context.

Through longitudinal studies on a targeted set of users, the collection of data pertaining to loneliness-specific constructs and behaviour may be analysed and modelled by employing machine learning techniques on large volumes of sensor information. Along with this analysis, virtual environments may be better designed in accordance with the structure of loneliness – especially given the rudimentary implementation of hypervigilance concepts that may not necessarily correlate effectively with hypervigilance experienced in real life scenarios – therefore allowing more effective treatment targeted towards individual needs. Additionally, the capacity to understand and recognise loneliness from this data further advantages diagnosis and treatment, rather than the identification of less relevant behaviour such as the encouraged meditative state, which only provides outcome-based insights as opposed to consistent behavioural measurements regarding patient progress. As such, more understanding about loneliness and its objective sensor data evaluation is essential for future work, especially as such information is largely unclear within the research community. Through this analysis, the sensors and processing techniques most valuable in a loneliness context may be identified and extracted for the development of sensor-embedded virtual reality devices as seen in industry and relevant literature[1,2,3,4] [20].

With a smaller amount of additional time, the acquisition of more user study participants may be prioritised given the minimal number utilised within evaluation of the developed application. While these limited studies demonstrated clear results that were evidenced across the population, a larger set of results is likely to ensure that interpretations are more reliable, and therefore more valid in their analysis. In this sense, such results would provide a valuable contribution to the research area, in which findings may be applied with more confidence.

External to loneliness applications, the examined studies employing similar technology applications often appear to accept the beneficial outcomes of virtual reality and sensors with minimal understanding regarding the reasons behind such success. Relevant within a wide scope of research domains, studies isolating the features of such systems in order to identify the causal factors of success would certainly be beneficial in identifying exactly how the concepts discussed within the review of literature affect the outcomes of their application, why they are effective, and what they contribute. This level of understanding has high potential in various applications of such technology and in advancing these respective fields further, in which findings may be incorporated into future developments such that they maximise efficacy according to their intended purpose.

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Appendix A

User study resources

Interview structure: rough outline of semi-structured interview topics and example questions, used within the final phase of the study to gather qualitative results.

Initial impressions:

- What were the overall impressions of the application?
- What do you think was the application's purpose?
- Have you learnt anything from the experience?
- Are there any noticeable outcomes as a result of application use?
- Did your experience or behaviours change over time?
- Do you think you were using features and functionality in the right way?

Sensor data:

- Why and how do you think data was being used?
- What do you think the sensors were measuring?
- Does the sensor data functionality function accurately and correctly?
- Is sensor data accurate, and does it function correctly according to physical behaviours?
- Do the sensors represent meditational movement?
- Is this use of sensor data acceptable, appropriate or trustable?

- How do you feel about this use of data?

Virtual environment and combination of technologies:

- How does the virtual game environment influence the experience?
- What do you think the virtual environment represents?
- Does the environment represent hypervigilance?
- Do sensors have an impact on the game or virtual environment?
- How do you think sensors influence the virtual game environment?
- Does sensor data influence the game in an appropriate way?
- Do sensor influence and virtual reality functionalities work together
- Are interactions in the game relevant and suitable?

Incorporation of literature:

- Would you use the strategies employed in the application in everyday life?
- Would you use the application over longer periods of time?
- Could these applications be beneficial or detrimental in practice?
- Could these applications have a significant impact?
- Would this usefulness or impact be different over prolonged use?
- Did you feel a sense of immersion and presence?
- Were you aware of the physical environment or external distractions?
- Do you think this experience would differ between individuals?
- Do you think the experience and outcomes are personalised towards individuals?
- Could future iterations of the application include different types of data?
- How could different types of data be beneficial?
- Could these applications help in the diagnosis and understanding of behaviours?

Demographic questionnaire: used within the first phase of the study to gather preliminary information about participants.

PRELIMINARY QUESTIONNAIRE

PARTICIPANT NUMBER:

1. What is your gender?					
MALE		FEMALE		OTHER	
2. What is your age range?					
18 – 24	25 – 29	30 – 34	35 – 39	40 – 50	OVER 50
3. Do you currently use any technology or applications for mental health?					
YES			NO		
If yes:	**3.1. Do these systems use or measure personal or non-personal data?**				
YES			NO		
	If yes:	**3.1.1. What type of data do these systems use or measure?**			
Answer:					
		3.1.2. How does the system use of measure this data?			
Answer:					
		3.2.3. Do you think this use of data is appropriate, and why?			
YES			NO		
Answer:					
6. How comfortable are you using technology that uses or measures behavioural data?					
Insecure	1	2	3	4	Comfortable
7. How comfortable are you using technology that uses or measures inertial data?					
Insecure	1	2	3	4	Comfortable
8. How familiar are you using virtual reality technology?					
Unfamiliar	1	2	3	4	Familiar

Sensor graphs: graphed accelerometer, gyroscope and gravity sensor data for every participant of the initial sensor study, used to determine which inertial smartphone sensor is most appropriate to determine slow movement states.

Appendix B

Python scripts

`client.py`: receives data from an Android smartphone server.

```python
import socket
import sys
import ast

s = socket.socket(socket.AF_INET, socket.SOCK_STREAM)
s.connect(('', 5555)) #removed IP address

def getSensor(data, item):
    return str(data[item]['value']).strip('[]')

while True:
    data = s.recv(1024).decode('utf-8')

    if (not data.startswith('[')) & (data != ''):
        data = ast.literal_eval(data)
        print('\nacc: ', getSensor(data, 'accelerometer'),
              '\ngra: ', getSensor(data, 'gravity'),
              '\ngyr: ', getSensor(data, 'gyroscope'))
    else:
        s.close()
        sys.exit('Server connection lost')
```

`server.py`: receives data from an Android smartphone client.

```
import socket
import sys
import ast

s = socket.socket(socket.AF_INET, socket.SOCK_STREAM)
print('Socket created')

try:
    s.bind(('', 5555)) #removed IP address
except socket.error as e:
    sys.exit('Socket bind failed: ' + str(e[0]) + ': ' + str(e[1]))
except:
    sys.exit('Socket bind failed: unforseen error')

print('Socket bind success')

s.listen(10)
print('Socket listening')

conn, addr = s.accept()

def getSensor(data, item):
    return str(data[item]['value']).strip('[]')

while True:
    data = conn.recvfrom(1024)[0].decode('utf-8')

    if (not data.startswith('[')) & (data != ''):
        data = ast.literal_eval(data)
        print('\nacc: ', getSensor(data, 'accelerometer'),
              '\ngra: ', getSensor(data, 'gravity'),
              '\ngyr: ', getSensor(data, 'gyroscope'))
    else:
        s.close()
        sys.exit('Client connection lost')
```

`server_storedata.py`: stores data from an Android smartphone client, used for sensor study analysis.

```
import socket
import sys
import ast

s = socket.socket(socket.AF_INET, socket.SOCK_STREAM)
print('Socket created')

try:
    s.bind(('', 5555)) #removed IP address
except socket.error as e:
    sys.exit('Socket bind failed: ' + str(e[0]) + ': ' + str(e[1]))
except:
    sys.exit('Socket bind failed: unforseen error')

print('Socket bind success')

s.listen(10)
print('Socket listening')

conn, addr = s.accept()

dAcc = ''
dGra = ''
dGyr = ''

def getSensor(data, item):
    return str(data[item]['value']).strip('[]')

def writeFile(dAcc, dGra, dGyr):
    acc = open('DATA\\P1\\accData.txt', 'a')
    acc.write(dAcc)
    acc.close()
    gra = open('DATA\\P1\\graData.txt', 'a')
    gra.write(dGra)
    gra.close()
    gyr = open('DATA\\P1\\gyrData.txt', 'a')
    gyr.write(dGyr)
    gyr.close()

while True:
    data = conn.recvfrom(1024)[0].decode('utf-8')

    if (not data.startswith('[')) & (data != ''):
        data = ast.literal_eval(data)
        print('\nacc: ', getSensor(data, 'accelerometer'),
```

```
                 '\ngra: ', getSensor(data, 'gravity'),
                 '\ngyr: ', getSensor(data, 'gyroscope'))

            dAcc += getSensor(data, 'accelerometer') + '\n'
            dGra += getSensor(data, 'gravity') + '\n'
            dGyr += getSensor(data, 'gyroscope') + '\n'
        else:
            writeFile(dAcc, dGra, dGyr)
            s.close()
            sys.exit('Client connection lost')
```

`sensor_data.ipynb`: graphs sensor data stored in given file locations, used for sensor study analysis (converted to Python file from Jupyter Notebook).

```
#!/usr/bin/env python
# coding: utf-8

# In[1]:


import pandas as pd
import matplotlib.pyplot as plt


# In[2]:


def getData(user, sensor, min = None, max = None):
    return pd.read_csv('DATA\\P' + str(user) + '\\' + sensor + 'Data.txt', names=['x', 'y', 'z'])[min:max]

def plotData(user, min = None, max = None):
    fig, axis = plt.subplots(1, 3)

    axis[0].plot(getData(user, 'acc', min, max))
    axis[0].set_title(getTitle('acc'))
    axis[0].set_xlabel('units of time (packet streams)')
    axis[0].set_ylabel('accelerometer value')
    axis[0].legend(['x', 'y', 'z'])

    axis[1].plot(getData(user, 'gra', min, max))
    axis[1].set_title(getTitle('gra'))
    axis[1].set_xlabel('packet streams over time')
    axis[1].set_ylabel('gravity sensor value')
    axis[1].legend(['x', 'y', 'z'])
```

```
    axis[2].plot(getData(user, 'gyr', min, max))
    axis[2].set_title(getTitle('gyr'))
    axis[2].set_xlabel('packet streams over time')
    axis[2].set_ylabel('gyroscope value')
    axis[2].legend(['x', 'y', 'z'])

    fig.subplots_adjust(wspace = 0.3)
    fig.set_figwidth(20)
    fig.set_figheight(5)

def markData(user, sensor, regions = None):
    plt.plot(getData(user, sensor))
    plt.title(getTitle(sensor))
    plt.xlabel('packet streams over time')
    plt.ylabel('gyroscope value')
    if regions != None:
        for i in regions:
            plt.axvspan(i[0], i[1], facecolor = 'r', alpha = 0.2)

def getTitle(sensor):
    if sensor == 'acc':
        return 'Accelerometer data'
    elif sensor == 'gra':
        return 'Gravity sensor data'
    elif sensor == 'gyr':
        return 'Gyroscope data'


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# ## PARTICIPANT 1

# In[3]:


plotData(1)


# In[4]:


markData(1, 'gyr', [[0, 8], [29, 32]])


# In[5]:
```

```
u1Gyr = getData(1, 'gyr', 0, 8).append(getData(1, 'gyr', 29, 32), ignore_index = True
    )
print('max: ' + str(max(u1Gyr.max())) + ', min: ' + str(min(u1Gyr.min())))


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# ## PARTICIPANT 2

# In[6]:


plotData(2)


# In[7]:


markData(2, 'gyr', [[56, 90]])


# In[8]:


u2Gyr = getData(2, 'gyr', 56, 90)
print('max: ' + str(max(u2Gyr.max())) + ', min: ' + str(min(u2Gyr.min())))


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# ## PARTICIPANT 3

# In[9]:


plotData(3)


# In[10]:


markData(3, 'gyr', [[36, 41]])

```

```
# In[11]:


u3Gyr = getData(3, 'gyr', 36, 41)
print('max: ' + str(max(u3Gyr.max())) + ', min: ' + str(min(u3Gyr.min())))


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# ## PARTICIPANT 4

# In[12]:


plotData(4)


# In[13]:


markData(4, 'gyr', [[26, 33], [89, 139]])


# In[14]:


u4Gyr = getData(4, 'gyr', 26, 33).append(getData(4, 'gyr', 89, 139), ignore_index =
    True)
print('max: ' + str(max(u4Gyr.max())) + ', min: ' + str(min(u4Gyr.min())))


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# ## PARTICIPANT 5

# In[15]:


plotData(5)


# In[16]:


```

```
markData(5, 'gyr', [[0, 28], [144, 149]])


# In[17]:


u5Gyr = getData(5, 'gyr', 0, 28).append(getData(5, 'gyr', 144, 149), ignore_index =
    True)
print('max: ' + str(max(u5Gyr.max())) + ', min: ' + str(min(u5Gyr.min())))


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# ## PARTICIPANT 6

# In[18]:


plotData(6)


# In[19]:


markData(6, 'gyr', [[0, 14], [56, 59]])


# In[20]:


u6Gyr = getData(6, 'gyr', 0, 14).append(getData(6, 'gyr', 56, 59), ignore_index =
    True)
print('max: ' + str(max(u6Gyr.max())) + ', min: ' + str(min(u6Gyr.min())))


# In[ ]:
```

Appendix C

Unity C# scripts

`Client.cs`: receives data from an Android smartphone server.

```
using System;
using UnityEngine;
using System.Net.Sockets;
using System.Threading;
using System.Text;

public class Client {
    public Vector3[] sensorData;

    #region Socket
    private const string IP = ""; //removed IP address
    private const int PORT = 5555;
    private TcpClient socketConnection;
    private Thread clientReceiveThread;
    #endregion

    public Client() {
        ConnectToTcpServer();
    }

    public void ConnectToTcpServer() {
        try {
            clientReceiveThread = new Thread(new ThreadStart(ListenForData));
            clientReceiveThread.IsBackground = true;
            clientReceiveThread.Start();
            Debug.Log("Socket listening");
        } catch(Exception e) {
            Debug.Log("On client connect exception " + e);
        }
    }
```

```

    private void ListenForData() {
        try {
            socketConnection = new TcpClient(IP, PORT);
            Byte[] bytes = new Byte[10240];
            Debug.Log("Connection successful");
            while(true) {
                using(NetworkStream stream = socketConnection.GetStream()) { //Create stream object for reading
                    int length;
                    while((length = stream.Read(bytes, 0, bytes.Length)) != 0) {
                        var incomingData = new byte[length]; //Read incoming stream into bytes array
                        Array.Copy(bytes, 0, incomingData, 0, length);
                        string serverMessage = Encoding.ASCII.GetString(incomingData); //Convert bytes array to string message

                        sensorData = GetSensorData(serverMessage); //Save json-formatted string into Vector3 values
                        Debug.Log("acc: " + sensorData[0] + ", gyro: " + sensorData[1]);
                    }
                }
            }
        } catch(SocketException socketException) {
            Debug.Log("Socket exception: " + socketException);
        }
    }

    private Vector3[] GetSensorData(string sJson) {
        string[] aJson = sJson.Split('[', ']');
        Vector3 accelerometer = StringToVector3(aJson[1]);
        Vector3 gyroscope = StringToVector3(aJson[3]);
        return new Vector3[] { accelerometer, gyroscope };
    }

    private Vector3 StringToVector3(string sVector) {
        string[] sArray = sVector.Split(',');
        return new Vector3(float.Parse(sArray[0]), float.Parse(sArray[1]), float.Parse(sArray[2]));
    }
}
```

`SensorManager.cs`: processes incoming sensor data.

```
using UnityEngine;
using UnityEngine.UI;

public class SensorManager : MonoBehaviour {
    public Client unityClient;

    #region Slowdown
    public Text text; //Displaying gyroscope value on screen (REMOVE AFTER TESTING)
    public GameObject panel;
    private bool slowMode = false;
    #endregion

    #region Enemies
    public GameObject enemySpawn;
    private EnemySpawn spawnScript;
    #endregion

    #region Gyroscope
    private Vector3 gyroscope;
    private float dummyXYZ = 8; //For testing
    bool temp = false; //For testing
    #endregion

    #region Timer
    private float timerDuration = 0.6f;
    private float timer;
    #endregion

    private void Awake() {
        spawnScript = enemySpawn.GetComponent<EnemySpawn>();
        gyroscope = Vector3.zero;
    }

    private void Start() {
        unityClient = new Client();
    }

    private void OnEnable() {
        timer = 0;
        slowMode = false;
    }

    private void Update() {
        GetData(); //DummyData();
        ChangeState();
    }
```

```

    private void GetData() {
        gyroscope = unityClient.sensorData[1];
        text.text = "Gyro: " + gyroscope.ToString();
    }

    private void DummyData() {
        //Generate vectors with consistently accelerating/decelerating values, for
            testing
        if(gyroscope.x >= 8f) temp = true;
        else if(gyroscope.x <= -8f) temp = false;
        if(temp) dummyXYZ -= 0.01f;
        else dummyXYZ += 0.01f;
        gyroscope = new Vector3(dummyXYZ, dummyXYZ, dummyXYZ);
        text.text = gyroscope.x.ToString();
    }

    private void ChangeState() {
        if(CheckSlowed()) {
            timer += Time.deltaTime;
        } else {
            timer = 0;
            if(slowMode) {
                slowMode = false;
                panel.SetActive(false);
                spawnScript.ChangeDifficulty(2f, 1.6f, 1.2f, 8);
            }
        }

        if(timer >= timerDuration) {
            slowMode = true;
            panel.SetActive(true);
            spawnScript.ChangeDifficulty(2.5f, 2f, 1.5f, 8);
        }
    }

    public bool CheckSlowed() {
        /*
        if(dummyXYZ < 3f && dummyXYZ > -3f) return true;
        else return false;
        //*/
        bool x = gyroscope.x <= 0.3f && gyroscope.x >= -0.15f;
        bool y = gyroscope.y <= 0.3f && gyroscope.y >= -0.15f;
        bool z = gyroscope.z <= 0.3f && gyroscope.z >= -0.15f;

        if(x && y && z) return true;
        else return false;
```

```
    }
}
```

`PlayerEvents.cs`: manages controller connections.

```
using System.Collections.Generic;
using UnityEngine;
using UnityEngine.Events;

public class PlayerEvents : MonoBehaviour {
    #region Events
    public static UnityAction OnTriggerDown = null;
    public static UnityAction OnTouchpadDown = null;
    public static UnityAction<OVRInput.Controller, GameObject> OnControllerSource =
        null;
    #endregion

    #region Anchors
    public GameObject leftAnchor;
    public GameObject rightAnchor;
    public GameObject headAnchor;
    #endregion

    #region Input
    private Dictionary<OVRInput.Controller, GameObject> controllerSets = null;
    private OVRInput.Controller inputSource = OVRInput.Controller.None;
    private OVRInput.Controller controller = OVRInput.Controller.None;
    private bool inputActive = true;
    #endregion

    private void Awake() {
        controllerSets = CreateControllerSets();
        OVRManager.HMDMounted += PlayerFound;
        OVRManager.HMDUnmounted += PlayerLost;
    }

    private void OnDestroy() {
        OVRManager.HMDMounted -= PlayerFound;
        OVRManager.HMDUnmounted -= PlayerLost;
    }

    private void Update() {
        if(!inputActive) return;

        CheckForController();
```

```
        CheckInputSource();
        Input();
    }

    private void CheckForController() {
        OVRInput.Controller controllerCheck = controller;

        //Find any right controller
        if(OVRInput.IsControllerConnected(OVRInput.Controller.RTrackedRemote)) {
            controllerCheck = OVRInput.Controller.RTrackedRemote;
        }

        //Find any left controller
        if(OVRInput.IsControllerConnected(OVRInput.Controller.LTrackedRemote)) {
            controllerCheck = OVRInput.Controller.LTrackedRemote;
        }

        //Use the headset if no controllers are available
        if(!OVRInput.IsControllerConnected(OVRInput.Controller.RTrackedRemote) &&
           !OVRInput.IsControllerConnected(OVRInput.Controller.LTrackedRemote)) {
            controllerCheck = OVRInput.Controller.Touchpad;
        }

        controller = UpdateSource(controllerCheck, controller);
    }

    private void CheckInputSource() {
        inputSource = UpdateSource(OVRInput.GetActiveController(), inputSource);
    }

    private void Input() {
        if(OVRInput.GetDown(OVRInput.Button.PrimaryIndexTrigger)) {
            if(OnTriggerDown != null) OnTriggerDown();
        }

        if(OVRInput.GetDown(OVRInput.Button.PrimaryTouchpad)) {
            if(OnTouchpadDown != null) OnTouchpadDown();
        }
    }

    private OVRInput.Controller UpdateSource(OVRInput.Controller check, OVRInput.Controller previous) {
        if(check == previous) return previous;

        GameObject controllerObject = null;
        controllerSets.TryGetValue(check, out controllerObject);
        if(controllerObject == null) controllerObject = headAnchor;
```

```
        if(OnControllerSource != null) OnControllerSource(check, controllerObject);
        return check;
    }

    private void PlayerFound() {
        inputActive = true;
    }

    private void PlayerLost() {
        inputActive = false;
    }

    private Dictionary<OVRInput.Controller, GameObject> CreateControllerSets() {
        Dictionary<OVRInput.Controller, GameObject> newSets = new Dictionary<OVRInput
            .Controller, GameObject>() {
            { OVRInput.Controller.LTrackedRemote, leftAnchor },
            { OVRInput.Controller.RTrackedRemote, rightAnchor },
            { OVRInput.Controller.Touchpad, headAnchor }
        };
        return newSets;
    }
}
```

`Pointer.cs`: manages pointer visualisations and button interactions.

```
using UnityEngine;
using UnityEngine.Events;

public class Pointer : MonoBehaviour {
    #region Pointer
    public float distance = 10.0f;
    public LineRenderer lineRenderer = null;
    public LayerMask everythingMask = 0;
    public LayerMask interactableMask = 0;
    public UnityAction<Vector3, GameObject> OnPointerUpdate = null;
    private Transform currentOrigin = null;
    private GameObject currentObject = null;
    #endregion

    #region Menu
    public GameObject menu;
    private MenuEnable menuScript;
    #endregion

    private void Awake() {
```

```
        menuScript = menu.GetComponent<MenuEnable>();
        PlayerEvents.OnControllerSource += UpdateOrigin;
        PlayerEvents.OnTriggerDown += ProcessTriggerDown;
        PlayerEvents.OnTouchpadDown += ProcessTouchpadDown;
        SetLineColour();
    }

    private void OnDestroy() {
        PlayerEvents.OnControllerSource -= UpdateOrigin;
        PlayerEvents.OnTriggerDown -= ProcessTriggerDown;
        PlayerEvents.OnTouchpadDown -= ProcessTouchpadDown;
    }

    private void Update() {
        Vector3 hitPoint = UpdateLine();
        currentObject = UpdatePointerStatus();
        if(OnPointerUpdate != null) OnPointerUpdate(hitPoint, currentObject);
    }

    private Vector3 UpdateLine() {
        RaycastHit hit = CreateRaycast(everythingMask);
        Vector3 endPosition = currentOrigin.position +  (currentOrigin.forward *
            distance);
        if(hit.collider != null) endPosition = hit.point;
        lineRenderer.SetPosition(0, currentOrigin.position);
        lineRenderer.SetPosition(1, endPosition);
        return endPosition;
    }

    private void UpdateOrigin(OVRInput.Controller controller, GameObject
        controllerObject) {
        currentOrigin = controllerObject.transform;
        if(controller == OVRInput.Controller.Touchpad) lineRenderer.enabled = false;
        else lineRenderer.enabled = true;
    }

    private GameObject UpdatePointerStatus() {
        RaycastHit hit = CreateRaycast(interactableMask);
        if(hit.collider) return hit.collider.gameObject;
        else return null;
    }

    private RaycastHit CreateRaycast(int layer) {
        Ray ray = new Ray(currentOrigin.position, currentOrigin.forward);
        Physics.Raycast(ray, out RaycastHit hit, distance, layer);
        return hit;
    }
```

```
    private void SetLineColour() {
        if(!lineRenderer) return;

        Color endColour = Color.white;
        endColour.a = 0.0f;
        lineRenderer.endColor = endColour;
    }

    private void ProcessTriggerDown() {
        if(!currentObject) return;

        Interactable interactable = currentObject.GetComponent<Interactable>();
        interactable.Pressed();
    }

    private void ProcessTouchpadDown() {
        menuScript.ToggleMenu(false);
    }
}
```

`Reticule.cs`: manages reticule visualisations.

```
using UnityEngine;

public class Reticule : MonoBehaviour {
    public Pointer pointer;
    public SpriteRenderer circleRenderer;

    public Sprite hoverOff;
    public Sprite hoverOn;

    private Camera m_Camera = null;

    private void Awake() {
        pointer.OnPointerUpdate += UpdateSprite;

        m_Camera = Camera.main;
    }

    private void OnDestroy() {
        pointer.OnPointerUpdate -= UpdateSprite;
    }

    private void Update() {
```

```
        transform.LookAt(m_Camera.gameObject.transform);
    }

    private void UpdateSprite(Vector3 point, GameObject hitObject) {
        transform.position = point;

        if(hitObject) circleRenderer.sprite = hoverOn;
        else circleRenderer.sprite = hoverOff;
    }
}
```

`EnemyShoot.cs`: manages enemy shooting behaviours.

```
using UnityEngine;
using UnityEngine.SceneManagement;

public class EnemyShoot : MonoBehaviour {
    private Camera main;
    public AudioSource shoot;

    #region Sensors
    private GameObject sensorManager;
    private SensorManager sensorScript;
    private bool slowMode = false;
    #endregion

    #region Scene
    private Scene scene;
    private bool sensorScene = false;
    #endregion

    #region Bullets
    private GameObject bullet;
    private GameObject tempBullet;
    private Rigidbody tempBulletRB;
    private float bulletSpeed = 3f;
    private float bulletDestroy = 3f;
    private bool first = true;
    #endregion

    #region Timer
    private float timerDuration = 2.5f;
    private float timer;
    #endregion

```

```
    private void Awake() {
        bullet = Resources.Load<GameObject>("BioTorpedoWhite");
        main = Camera.main;

        //if(SceneManager.GetActiveScene().name == "Test") {
        if(SceneManager.GetActiveScene().name == "SensorsVR") {
            sensorScene = true;
            sensorManager = GameObject.FindWithTag("Sensor");
            sensorScript = sensorManager.GetComponent<SensorManager>();
            slowMode = sensorScript.CheckSlowed();
            if(slowMode) ChangeDifficulty(3.5f, 1f, 10f);
        }
    }

    private void Update() {
        transform.LookAt(main.transform);

        if(sensorScene) ChangeState();

        timer -= Time.deltaTime;
        if(timer > 0) return;
        timer = timerDuration;
        Shoot();
    }

    private void Shoot() {
        if(first) {
            first = false;
            timer = 0.9f;
            return;
        }
        tempBullet = Instantiate(bullet, transform.position, transform.rotation);
        tempBulletRB = tempBullet.GetComponent<Rigidbody>();
        tempBulletRB.AddForce(tempBulletRB.transform.forward * bulletSpeed, ForceMode
            .Impulse);
        shoot.Play();
        Destroy(tempBullet, bulletDestroy);
    }

    private void ChangeState() {
        if(slowMode != sensorScript.CheckSlowed()) {
            if(!slowMode) ChangeDifficulty(3.5f, 1f, 10f);
            else ChangeDifficulty(2.5f, 3f, 3f);
        }
        slowMode = sensorScript.CheckSlowed();
    }

```

```
    public void ChangeDifficulty(float newCooldown, float newBulletSpeed, float
        newBulletDestroy) {
        timerDuration = newCooldown;
        bulletSpeed = newBulletSpeed;
        timer = timerDuration;
    }
}
```

`EnemySpawn.cs`: manages enemy spawning behaviours.

```
using UnityEngine;
using UnityEngine.UI;

public class EnemySpawn : MonoBehaviour {
    public Text text;

    #region Enemies
    public GameObject enemy;
    private Vector3 spawnPosition;
    private int maxEnemies = 8;
    private int enemyNumber = 0;
    private int enemiesShot = 0;
    private float enemyRadius = 0.2f;
    private float area = 0;
    #endregion

    #region Audio
    private AudioSource[] sounds;
    private AudioSource shoot;
    private AudioSource destroy;
    #endregion

    #region Timer
    private float timerDuration;
    private float timer;
    private float slowCooldown = 2f;
    private float mediumCooldown = 1.6f;
    private float fastCooldown = 1.2f;
    #endregion

    private void Awake() {
        sounds = GetComponents<AudioSource>();
        shoot = sounds[0];
        destroy = sounds[1];
    }
```

```

    private void OnEnable() {
        text.text = "0";
        enemiesShot = 0;
        enemyNumber = 0;
        timerDuration = 1f;
        timer = timerDuration;
    }

    private void Update() {
        timer -= Time.deltaTime;
        if(timer > 0) return;
        timer = timerDuration;
        Spawn();
    }

    private void Spawn() {
        if(enemyNumber >= maxEnemies) return;

        area = Random.Range(0f, 1f);
        if(area < 0.25f) spawnPosition = new Vector3(Random.Range(-2f, -3.5f), Random
            .Range(0.7f, 1.8f), Random.Range(0f, 2f));
        else if(area > 0.75f) spawnPosition = new Vector3(Random.Range(2f, 3.5f),
            Random.Range(0.7f, 1.8f), Random.Range(0f, 2f));
        else spawnPosition = new Vector3(Random.Range(-2.5f, 2.5f), Random.Range(0.7f
            , 1.8f), Random.Range(1.5f, 3f));

        if(!CheckCollision(spawnPosition, enemyRadius)) {
            GameObject e = Instantiate(enemy, spawnPosition, Quaternion.Inverse(
                Quaternion.identity));
            e.GetComponent<Interactable>().spawnScript = gameObject.GetComponent<
                EnemySpawn>();
            e.GetComponent<EnemyShoot>().shoot = shoot;
        } else {
            Spawn();
            return;
        }
        IncrementEnemies(1);
    }

    private bool CheckCollision(Vector3 center, float radius) {
        Collider[] hitColliders = Physics.OverlapSphere(center, radius);
        if(hitColliders.Length > 0) return true;
        else return false;
    }

    private void IncrementEnemies(int increment) {
```

```
        enemyNumber += increment; //External functions may pass -1 when enemies are destroyed
        if(enemyNumber < 3) timerDuration = fastCooldown;
        else if(enemyNumber < 6) timerDuration = mediumCooldown;
        else timerDuration = slowCooldown;
        timer = timerDuration;
    }

    public void ShootEnemy() {
        IncrementEnemies(-1);
        enemiesShot += 1;
        destroy.Play();
        text.text = enemiesShot.ToString();
    }

    public void ChangeDifficulty(float newSlowCooldown, float newMediumCooldown, float newFastCooldown, int newMaxEnemies) {
        slowCooldown = newSlowCooldown;
        mediumCooldown = newMediumCooldown;
        fastCooldown = newFastCooldown;
        maxEnemies = newMaxEnemies;
        //timer = timerDuration;
    }
}
```

`Interactable.cs`: defines interactable properties for the attached object.

```
using UnityEngine;

public class Interactable : MonoBehaviour {
    public EnemySpawn spawnScript;

    public void Pressed() {
        GetComponent<Renderer>().material = null;
        spawnScript.ShootEnemy();
        Destroy(gameObject, 0.15f);
    }
}
```

MenuEnable.cs: transitions between menu and gameplay states.

```
using UnityEngine;
using UnityEngine.SceneManagement;

public class MenuEnable : MonoBehaviour {
    private bool sensorScene = false;

    #region Toggle
    public Canvas menuCanvas;
    public Canvas gameCanvas;
    public GameObject panel;
    public GameObject sensorManager;
    public GameObject enemySpawn;
    public GameObject cameraRig;
    private UserCollider cameraCollider;
    #endregion

    public void Awake() {
        cameraCollider = cameraRig.GetComponent<UserCollider>();
        if(SceneManager.GetActiveScene().name == "SensorsVR") sensorScene = true;
    }

    private void OnEnable() {
        ToggleMenu(true);
    }

    public void ToggleMenu(bool enable) {
        menuCanvas.enabled = enable;
        gameCanvas.enabled = !enable;
        cameraCollider.enabled = !enable;
        if(sensorScene) {
            sensorManager.SetActive(!enable);
            if(enable) panel.SetActive(false);
        }
        enemySpawn.SetActive(!enable);

        if(enable) {
            GameObject[] enemies = GameObject.FindGameObjectsWithTag("Enemy");
            foreach(GameObject e in enemies) Destroy(e);
        }
    }
}
```

`UserCollider.cs`: manages collision events and user health.

```
using System.Collections;
using UnityEngine;
using UnityEngine.UI;

public class UserCollider : MonoBehaviour {
    private AudioSource hit;

    #region UI
    public GameObject panel;
    public Slider healthBar;
    private int health;
    #endregion

    #region Menu
    public GameObject menu;
    private MenuEnable menuScript;
    #endregion

    private void Awake() {
        hit = GetComponent<AudioSource>();
        menuScript = menu.GetComponent<MenuEnable>();
        healthBar = healthBar.GetComponent<Slider>();
    }

    private void OnEnable() {
        health = 100;
    }

    private void Update() {
        healthBar.value = health;
    }

    private void OnTriggerEnter(Collider other) {
        Destroy(other.gameObject, 0.1f);
        if(health > 0) {
            health -= 5;
        }
        StartCoroutine(DamageEffect());
        if(health <= 0) {
            menuScript.ToggleMenu(true);
        }
        hit.Play();
    }

    private IEnumerator DamageEffect() {
        panel.SetActive(true);
```

```
        yield return new WaitForSeconds(0.3f);
        panel.SetActive(false);
    }
}
```