Greenbeing: Understanding the Intersection of Greenness and Mental Wellbeing Through the Use of Ecological Momentary Assessment

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Executive Summary

The relationship between time spent within greenspaces and mental wellbeing has long been acknowledged by humans, and the roots of this relationship have been suggested to herald from our ancestral past. Even so, this relationship is still studied widely in an attempt to unearth the wide variety of influences on this relationship such that meaningful decisions can be made in urban planning and for mental health interventions. Through a comprehensive review of literature and empirical data collection from individuals living in the UK, this study offers insights into the mediating factors of this relationship, and contributes a novel insight in terms of the interaction of workplace greenness in this relationship.

Research Questions

1. Is there an association between being amongst greenness and mental wellbeing?

2. How does gender mediate the relationship between being amongst greenness and mental wellbeing?

3. How does the greenness of an individual's workplace mediate the relationship between being amongst greenness and mental wellbeing?

Contribution

- I researched and gathered literature informing an EMA based study.
- I developed an EMA system in Java from the ground up, utilising industry standard APIs to do so.
- I endeavoured to provide a meaningful contribution to the literature base, based on previously identified research gaps.

Acknowledgements

I would like to extend my gratitude to my supervisor Dr Jon Bird, for his support and assistance in navigating this project. I would also like to thank Jim for his advice and guidance when it came to the statistical analysis, and Jane for her constructive feedback and moral support.

Author's Declaration

I declare that the work in this dissertation was carried out in accordance with the requirements of the University's Regulations and Code of Practice for Taught Programmes and that it has not been submitted for any other academic award. Except where indicated by specific reference in the text, the work is the candidate's own work. Work done in collaboration with, or with the assistance of, others, is indicated as such. Any views expressed in the dissertation are those of the author.

Oscar Dilkes
12 December 2023

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1 Introduction

The positive relationship between time spent in greenspaces and mental wellbeing is well documented, with studies showing a direct and clear link between time spent in parks and forests with positive emotions. However, a range of gaps exist in understanding the direct causative factors, and also in other factors which may impact the efficacy of time forest bathing in relation to positive mental wellbeing. Inherent methodological issues exist with many studies which attempt to understand these relationships. These studies often involve placing people in a study environment or setting, which inevitably impacts results. Confirmation bias is rife when people are consciously aware of the purpose of the study when what they are doing is inherently out of place in comparison to the way these individuals would typically experience green space, thus, finding a way which we can measure this relationship and other factors impacting this relationship is surely beneficial.

Ecological momentary assessment (EMA) is one possible solution to this methodological issue. EMA is a method of collecting data while participants are carrying out a normal day and existing in their typical environments, and benefits from the ability to obtain data during or near to the time of a participant exhibiting the behavior you're interested in understanding. Specifically beneficial is the ability to collect data through a participant's smartphone, which means that this method is relatively unintrusive in comparison to other data collection techniques. Furthermore, the repeated nature of EMA provides you with detailed information that tracks over time so you can notice gradual changes in participant behavior.

EMA solves two potential issues that exist in this area; the reduction of recall bias which may be present when collecting data using traditional surveys or interviews, and the reduction of confirmation bias which may be present when participants are placed in unusual environments for the purpose of study, and are thus hyper aware of the conditions of their participation. Although EMA could be argued to be intrusive due to its integration with a participant's regular life, studies are often limited in duration and questions are typically succinct. This integration into a participant's life is part of what makes EMA such a promising research method, and whilst it could be argued that confirmation bias is still present due to the novelty of a participant completing an assessment in contrast to their normal life, the nature of EMA seeks to reduce this significantly in comparison to other invasive methods.

This work seeks to investigate the relationship between time spent in greenspaces and mental wellbeing by using EMA, and suggests where EMA could prove particularly beneficial in terms of insights into this particular field.

Dr Jon Bird approved that this study was covered by blanket ethics application 12046.

1.1 Definitions

Greenbathing The intentional immersion of oneself in a natural environment with the goal of relaxation and achieving mental clarity.

Greenspace An area of significant grass and/or vegetative cover; extends from parks, to nature reserves.

Mental Wellbeing A bifold representation of both how an individual feels and how well they are able to function.

2 Background

This section aims to provide context behind the primary matters at hand, Ecological Momentary Assessment (EMA), and the study of the relationship between greenbathing and mental wellbeing. All following subsections provide a history of these matters leading up to the 21st century, allowing the literature review to provide a more substantiated breakdown of contemporary research concerning the two, on the basis that the turn of the 21st century brought with it a variety of technologies and technological advancement that heralds the current era of research for both of these matters. This background begins with an exploration of the history of the study of greenbathing greenspaces, with the goal that based on a thorough understanding of how this has developed, by subsequently developing an understanding of EMA the potential of EMA in the research of this relationship will be considered.

2.1 The Study of the Relationship between Greenbathing and Mental Wellbeing

The relationship between greenbathing and mental wellbeing has been well documented, and it has been considered throughout human history. Presented often as an innate factor of being human, greenbathing enhancing mental clarity and improving mental wellbeing makes perfect sense; we are used to residing in greenspaces biologically – urbanisation did not exist until humans did. Varying degrees of correlation have been shown in studies, which highlights the complexity of this relationship, with a variety of factors influencing the efficacy of greenbathing on improving mental wellbeing, something which studies towards the end of the 20th century sought to understand better.

The overall effect that time spent in greenspaces has on mental wellbeing has been acknowledged historically, with the stoicism school of philosophy placing a particular emphasis on the participation in, and understanding of, nature [Fabjański and Brymer 2017; Richardson 1980] – although this also refers to far more than just greenspaces. A more contemporary angle on this can be seen with the Japanese practice of *shinrin-yoku*, the immersing of oneself in nature whilst paying particular thought to ones surroundings and how nature interacts with itself [Q. Li 2018; Miyazaki 2018]. This section gives a history of this study, and highlights methodologies used to understand this relationship.

Throughout the 19th and 20th centuries, the Industrial Revolution catalysed rapid urbanisation leading to growing concerns about the health impacts of living in polluted and densely populated areas within cities. This gave rise to the intentional planning of parks and greenspaces within cities and amongst those densely populated areas, as a way to combat some of the negative effects of living in a heavily industrialised society. Whilst this was initially a response to some of the physical impacts of living in such a society, the significance of these greenspaces in terms of positive mental wellbeing was quickly noted [R. Hunter 1886; Rauch 1869]. In Harlem, New York, it was noted that beyond the impacts that walking through these greenspaces had on physical wellbeing, they also had an influence on the "manners, the morals, the imagination" of those who took advantage of them [Mullaly 1887].

Although this interest subsequently stagnated, the years following World War II heralded a surge in suburban development occurring as a response to the subsequent baby boom, but also as a means to rehouse people who had lost their homes due to intense bombing. Alongside this surge in suburban development was a renewed interest in urban planning, and an opportunity to readdress how planners approached the design of neighbourhoods with the best interest of the people at concern. Researchers increasingly studied the role of urban greenspaces and their relationship with mental wellbeing, and incorporated their findings into how they built and organised new housing developments [Madge 1950; Mumford 1956]. Some studies acknowledged the lasting impact of widespread adoption of personal automobiles on city planning and available greenspaces, one such paper noting that while suburban train stations were once surrounded by large volumes of space, these areas had been filled in over time, with green spaces increasingly being replaced by car parking spaces [Blumenfeld 1949].

This increasing interest in urban planning gave rise to the emergence of environmental psychology as a field in the 1960s, which demarcated a new era in this study leading up to the 21^{st} century. This encouraged increasingly widespread study on the relationship between greenspaces and mental wellbeing, now with a more particular focus on the matter and the opportunity to hone in on the variety of factors that mediate this relationship. For example, a variety of studies aimed to understand the influence of urban greenspace as a location for social interaction on mental wellbeing [Coley, Sullivan, and Kuo 1997; Kweon, Sullivan, and Wiley 1998], whilst other studies investigated factors such as socioeconomic status [Bonaiuto, Aiello, Perugini, Bonnes, and Ercolani 1999; Holahan 1976] or noise reduction [Beard and R. L. Green 1994; Bolund and Hunhammar 1999; Tyrväinen 1997].

2.2 Ecological Momentary Assessment

EMA, also known as the Experience Sampling Method (ESM), is a research technique that captures real-time data at the precise moment and environment of a specific behaviour under study. EMA offers various methods for researchers to observe or gather responses to the targeted behaviour, most commonly through short-form surveys or open-ended questions. These questions enable participants to express their immediate feelings and thoughts. EMA is lauded for addressing issues inherent in traditional research methods, though it is not without its challenges. However, recent advancements in technology, particularly the widespread use of smartphones and wearable devices, have mitigated many of these difficulties. As a result, EMA has become more viable and effective than ever before. This subsection delves deeper into the background of EMA as a research method, underscoring its significant and growing relevance in research.

2.2.1 History

EMA was founded in the 1960s within the psychology field, with the primary goal of tracking changes in participant thoughts, feelings, and behaviours over time [Hektner, Schmidt, and Csikszentmihalyi 2007]. Early EMA methods utilised simple tools like pen and paper for response tracking and stopwatches for time-stamping [A. S. Green, Rafaeli, Bolger, Shrout, and Reis 2006; S. Shiffman, Stone, and Hufford 2008]. This approach marked a significant shift from previous research methodologies, which either relied on controlled laboratory settings or retrospective participant accounts, which introduced significant recall bias to responses [S. Shiffman, Stone, and Hufford 2008]. EMA has evolved significantly over time, seeing considerable changes in the way with which it is utilised, and techniques used in the development of EMA systems. Technological advancements have been the primary catalyst for this evolution, building on the flexibility of EMA applications, data collection methods, and the types of data gathered. The digital technology boom of the 1980s heralded a new era for EMA. Furthermore, the introduction of handheld computers and electronic diaries brought about greater flexibility, participant guidance, compliance, and simplified time stamping and scheduling [Perrine, Mundt, Searles, and Lester 1995; S. Shiffman, Paty, Gnys, Kassel, and Hickcox 1996].

The 1990s saw further advancements with the widespread adoption of email and the internet. This allowed for more efficient and reliable scheduling and deployment of EMA systems, meaning that EMA no longer required relative physical proximity, and global studies were now possible [S. Shiffman, Stone, and Hufford 2008]. However, the most significant leap in EMA's capabilities came with the rise in mobile phone use in the early 2000s. Mobile phones enabled real-time adaptation of EMA systems in response to user input, extending their reach to remote locations [Hektner, Schmidt, and Csikszentmihalyi 2007]. These developments have been compounded by the widespread adoption and use of smartphones, which further revolutionised EMA [L. P. De Vries, Baselmans, and Bartels 2021]. With cellular internet capabilities, smartphones allow for the collection of diverse data types, including images and videos [Colombo, Fernández-Álvarez, Patané, Semonella, Kwiatkowska, García-Palacios, Cipresso, Riva, and Botella 2019; Runyan and Steinke 2015]. The personalization of EMA systems to individual participant needs, the ability to adapt data requirements on the go, and the accessibility of smartphones have all enabled EMA to become one of, if not the most versatile research method available to researchers today [Colombo, Fernández-Álvarez, Patané, Semonella, Kwiatkowska, García-Palacios, Cipresso, Riva, and Botella 2019; Dao, De Cocker, Tong, Kocaballi, Chow, and Laranjo 2021; Heron and Smyth 2010]. Even in more recent years, technological advancements have increased the versatility and robustness of EMA as a research method. The rise of wearable technology has further integrated EMA into participants' daily lives [Brannon, Cushing, Crick, and T. B. Mitchell 2016; Colombo, Fernández-Álvarez, Patané, Semonella, Kwiatkowska, García-Palacios, Cipresso, Riva, and Botella 2019; Tutunji, Kogias, Kapteijns, Krentz, Krause, Vassena, and Hermans 2021]. Wearables offer a more seamless experience, reducing the intrusiveness often associated with retrieving mobile devices. This development has led to more natural and less inhibited data collection, reflecting a closer representation of participants' true psychological states.

With all of this, it is clear that EMA has a promising future in terms of its further development alongside technological progression, but also in terms of the range of applications it is used for as a wider variety of fields of research and even businesses recognise how invaluable it can be as a research tool.

2.2.2 Strengths

As discussed prior, EMA offers a variety of strengths in comparison to other existing research methods. One such strength is the ability EMA has to provide insights into the precise context in which the focused behaviours are being exhibited [Stone and S. S. Shiffman 2010; Timmer, Hickson, and Launer 2017]. By asking participants questions whilst they are in the exact physical environment and affective state in which these behaviours are taking place, they are better able to provide insights into the environmental and situational factors which may influence their responses. This is referred to as ecological validity. Due to the fact that EMA traditionally takes place in the naturalistic settings of participants as opposed to in laboratories or controlled studies, the responses given by participants reflect more accurately their day to day experiences. Another strength of EMA is thanks to its inherently longitudinal nature, in that it is well suited to understanding and studying dynamic processes and changes over time, providing researchers with long term data alongside contextual information which can aid in analysing and proposing statistically significant relationships between the affective state of participants and the behaviour or setting in question [L. P. De Vries, Baselmans, and Bartels 2021; Enkema, McClain, Bird, Halvorson, and Larimer 2020].

Somewhat related to this is the cost efficiency of EMA in collecting that longitudinal data. If you rely on users using their smartphones to engage with the EMA, you immediately save a huge amount of money in terms of providing users with the means with which to participate in the study [L. P. De Vries, Baselmans, and Bartels 2021]. Hypothetically, all a researcher needs to do is develop the EMA system, run the EMA system, and store data, which within small to medium sized studies can be an incredibly cost effective way to collect data. In terms of participant satisfaction, EMA is linked with two key strengths, the first of which being its ability to enhance participant engagement and satisfaction [Colombo, Fernández-Álvarez, Patané, Semonella, Kwiatkowska, García-Palacios, Cipresso, Riva, and Botella 2019]. Since EMA is inherently interactive, this can bring increased participant interest, which improves data quality and also participant compliance. Furthermore, the relative ease of integrating a reward system or immediate participant feedback can increase engagement and thus compliance, compounding these benefits.

This takes us onto the second of these strengths, which is the ability to personalise EMA studies and tailor them to the needs of each individual participant. Not only does this improve participant engagement as it gives participants the freedom to tailor their experience of the EMA to their own personal needs, within the bounds the researcher may set, but it also allows researchers to tailor the EMA to each participant such that individual differences are accounted for, which is especially beneficial when EMA is used in clinical settings [Colombo, Fernández-Álvarez, Patané, Semonella, Kwiatkowska, García-Palacios, Cipresso, Riva, and Botella 2019; H. Zhang, Ibrahim, Parsia, Poliakoff, and Harper 2023].

The primary strength with which EMA is associated, however, is its ability to reduce recall bias [S. Shiffman, Stone, and Hufford 2008]. By asking participants to initiate the EMA at the time at which the studied behaviour is being exhibited, there is effectively zero recall bias introduced to their responses, with participants giving the most accurate account of how they feel at that exact moment. This, in combination with its ecological validity, positions EMA in a unique spot within the spectrum of research methods available to researchers.

Finally, the strength which gives EMA such high potential is its accessibility [L. P. De Vries, Baselmans, and Bartels 2021; S. Shiffman, Stone, and Hufford 2008]. The majority of people in the world have access to or own a smartphone, and most of those people have access to cellular data, which means that EMAs can be deployed in any ecological setting, opening it up to a highly diverse range of possible fields of study. Furthermore, utilising smartphones as a means of undertaking EMA means that there is high flexibility in the types of data which can be collected, which could include location data, images and videos, audio, and also integration with social media or even fitness trackers.

2.2.3 Weaknesses

Whilst EMA does have a wide variety of strengths that solve various epistemological problems present in other research methods, these do not come without significant weaknesses in comparison to these other methods. Participant burden can be a significant challenge that counteracts the opposing benefits that EMA can provide in terms of participant satisfaction and engagement. By frequently prompting participants to respond to the EMA, it can become tedious and onerous, which can lead to response fatigue and reduced compliance, both of which can prove of significant detriment to data collection and the quality of the data gathered [S. Shiffman, Stone, and Hufford 2008].

Furthermore, the act of repeatedly measuring and observing behaviours can influence the behaviours you are attempting to understand and study [Hufford 2007; S. Shiffman, Stone, and Hufford 2008]. EMA participants may change their natural responses subconsciously or even consciously since they are aware that they are being observed, which can also prove detrimental to data quality. Another potential issue in terms of data quality is the variety of psychological and ecological factors which can have an impact on participant responses, particularly those beyond the scope of the study in question. It would be infeasible, or at least highly expensive, for an EMA study to account for every single possibility, and to expect the participant to give every single tiny piece of context, so some level of uncertainty and unmeasured bias creeping into data is an inevitability.

A final weakness associated with EMA, and especially with contemporary EMA, is in the reliability of technology [Burke, S. Shiffman, Music, Styn, Kriska, Smailagic, Siewiorek, Ewing, Chasens, French, et al. 2017]. Typical modern EMA studies rely on the use of smartphones or wearables, both of which come loaded with common issues, such as limited battery life, software glitches, and connectivity problems, which can have a significant impact on the ability to collect data, alongside limiting the scope of settings within which EMA studies can take place. All this being said, EMA has a high potential as a methodology and shows promise in data collection for a variety of purposes, even alongside existing datasets from other research techniques, presenting itself possibly as a supplementary research method.

2.2.4 Existing Applications

Ecological Momentary Assessment (EMA) has significantly impacted various fields, notably health, psychology, and social sciences by providing real-time, enriched data that produces well informed insights into these fields.

EMA is a key tool used in health and psychology, and is used frequently for studying mood disorders, anxiety, stress, and coping mechanisms [S. Shiffman, Stone, and Hufford 2008]. Its ability to provide real-time data on patient and participant health helps doctors and researchers evaluate the efficacy of therapeutic interventions. Furthermore, this helps particularly when studying addiction, as it can identify particular triggers or trends in an individual's life that may trigger addictive behaviour or relapses. This can be applied to chronic illnesses such as diabetes or asthma; understanding how and when symptoms fluctuate can help enable better treatment in future. In social sciences, EMA has been used to enlighten researchers on social interaction, helping to understand the dynamics of social networks and how they function. Furthermore, it has helped to understand family dynamics from an objective and unobtrusive angle, and has helped to understand cultural norms and how they are exhibited in particular circumstances [Wrzus and Neubauer

2023].

2.3 Summary

In providing sufficient context for both the understanding of the relationship between walking in green space and mental wellbeing, and Ecological Momentary Assessment, the rationale for this study should now be clear. EMA is well aligned to research in this area, and its high ecological validity paired with its minimal recall bias suit it well to understanding how people's emotions change whilst immersed in greenspace.

3 Literature Review

3.1 Contextual Literature Review

3.1.1 Mediating Factors

Recent studies have focused on the range of factors which mediate the relationship between greenspaces and mental wellbeing, which are commonly identified as social cohesion, noise reduction, physical activity, attention restoration, and stress recovery [A. Dzhambov, Hartig, Markevych, Tilov, and D. Dimitrova 2018; Wang, Helbich, Y. Yao, J. Zhang, P. Liu, Yuan, and Y. Liu 2019]. Whilst there is considerable interplay amongst these factors, the ability of greenspace to reduce stress is most commonly acknowledged, due in part to the fact that all other identified mediators play a part in stress reduction; for this reason, the impact on stress is discussed both throughout this subsection and at the end.

Whilst there is a lack of consensus on a clear definition of social cohesion [Clarke, Wallace, Cadaval, E. Anderson, Egerer, Dinkins, and Platero 2023], it has been proposed by Schiefer et al. that there are six dimensions of social cohesion that are common and routinely referred to: social relations, identification, orientation towards the common good, shared values, quality of life, and equality [Schiefer and Van der Noll 2017]. These measures are consistent with existing literature on social cohesion within greenspaces [Giannico, Spano, Elia, D'Este, Sanesi, and Lafortezza 2021; Jennings and Bamkole 2019; Stewart 2020], although there is a need to substantiate the literature base on what components of a greenspace contribute to social cohesion and its common dimensions [Jennings and Bamkole 2019; R. Zhang, C.-Q. Zhang, and Rhodes 2021]. This being said, components common in greenspaces that improve social cohesion include sporting facilities, play parks, benches, and footpaths. Whilst these may serve to particular social activities, such as arranging to meet existing friends to play sports, walk together, or sit together, they also facilitate small talk and casual interactions amongst strangers, creating a sense of familiarity and thus community [Elands, Peters, and De Vries 2018]. Social cohesion in greenspaces, then, is acquired through maintaining and improving existing relationships, but also through making new ones. This functions to alleviate stress through the maintenance of meaningful relationships and a sense of community, making individuals feel comfortable in their surroundings, building a support network, and providing the opportunity to alleviate stress via social interaction.

Noise pollution is identified as one of the key types of pollution in urban environments, and contributes to negative mental wellbeing for a variety of reasons, including the disruption of sleep, stress, annoyance, and distraction, leading to a loss of focus [A. M. Dzhambov and D. D. Dimitrova 2014; Öhrström 2004]. Whilst there are a variety of methods to reduce noise exposure, for example, the construction of sound reduction barriers, these are widely regarded as unattractive and artificial, which can interfere with some of the reasons for reducing noise levels in the first place, such as reducing annoyance and stress. The use of increased roadside vegetation is a common technique used by urban planners in reducing noise and functions through the absorption, reflection, diffraction, and interference of sound waves [L. Anderson 1984; A. M. Dzhambov and D. D. Dimitrova 2014]. Whilst the construction of entire greenspaces with the primary goal of noise reduction is uncommon, this is often viewed as a secondary benefit of the creation and maintenance of greenspaces. Reduced noise pollution relieves stress by enabling individuals to have better sleep, reducing distractions from important tasks, and simply by being quieter: Westman and Walters claim that “the fundamental purposes of hearing are to alert and warn", and show that unnecessary noise can trigger defensive responses and fight or flight mechanisms [Westman and Walters 1981].

Whilst many greenspaces are built with physical activity in mind, they are often considered preferable locations for physical activity regardless of whether particular sporting facilities are present. Giles-Corti et al. showed that individuals who walk more had better accessibility to large open greenspaces [Giles-Corti, Broomhall, Knuiman, Collins, Douglas, Ng, Lange, and Donovan 2005], whilst Coombes et al. showed in a study on the relationship between parks and greenspaces that those who lived closer to formally designated parks were more likely to engage in physical activity [Coombes, Jones, and Hillsdon 2010]. Furthermore, the relationship between physical activity and mental wellbeing is well documented, with physical activity being routinely shown to reduce anxiety, improve self-image, and catalyses the release of beta-endorphins, which reduce cortisol levels, indicating lower stress [Fox 1999].

Attention Restoration Theory (ART) is a theory first proposed by Rachel and Stephen Kaplan which suggests that natural environments have the potential to restore focus and improve cognitive ability [Kaplan 1995; Ohly, White, Wheeler, Bethel, Ukoumunne, Nikolaou, and Garside 2016; Stevenson, Schilhab, and Bentsen 2018]. ART proposes four key components of natural environments that create this effect: Being away, Fascination, Extent, and Compatibility [Kaplan 1995]. Being away refers to the mental distance from an individual's normal activities, which helps reduce fatigue. Fascination refers to an involuntary form of attention that doesn't deplete cognitive resources; inherently fascinating stimuli found in natural environments distract the mind from its current concerns. Extent refers to the idea that natural environments are both rich and coherent enough for individuals to get lost in their surroundings without distraction, and forget any worries. Finally, compatibility refers to the compatibility of a natural environment to the needs of an individual, for example, a quiet park may be more conducive to relaxation, whereas a busier park may be more conducive to stimulation, and thus distraction.

Attention restoration reduces stress in several ways. It enables the realignment of thought processes, and can distract an individual from stressors in their lives. Furthermore, physical distance and psychological distance from those stressors also alleviates stress.

Throughout the available literature, stress recovery presents itself as a sort of central mediator amongst all these factors, whilst simultaneously mediating the relationship between greenbathing and mental wellbeing independently. Tyrväinen et al. showed that greenbathing within urban park and woodland had a positive impact on stress relief, through a highly controlled study that involved placing participants in deck chairs in various urban environments [Tyrväinen, Ojala, K. Korpela, Lanki, Tsunetsugu, and Kagawa 2014]. Another study by Olafsdottir et al. showed that walking in nature had a restorative effect on cortisol levels, and resulted in lower cortisol levels than the other tested isolated activities, that is, viewing nature and treadmill walking inside [Olafsdottir, Cloke, Schulz, Van Dyck, Eysteinsson, Thorleifsdottir, and Vögele 2020]. These studies are not alone, with a wide variety of additional studies using various methodologies showing stress recovery in greenspaces (Aziz et al., 2021).

3.1.2 Urban Greenspace

Many contemporary studies have reinforced the existing literature base showing a positive association between urban greenbathing and mental wellbeing [Akpinar, Barbosa-Leiker, and Brooks 2016; Ha, Kim, and With 2022; Houlden, Porto de Albuquerque, Weich, and Jarvis 2021; R. Mitchell 2013; Nutsford, Pearson, and Kingham 2013; A. E. Van den Berg, Maas, Verheij, and Groenewegen 2010; Wood, Hooper, Foster, and Bull 2017].This being said, the consistency of results using varying results in similar circumstances has rarely been measured, other than a key paper that utilised a variety of measures to understand this relationship written by Triguero-mas et al., which showed a positive association for each of these measures, alongside showing that surrounding greenness had a more significant impact on mental wellbeing than access to greenness did [Triguero-Mas, Dadvand, Cirach, Martínez, Medina, Mompart, Basagaña, Gražulevičienė, and Nieuwenhuijsen 2015]. In considering the key mediators identified previously, they failed to show an association between greenspace and social contact or physical activity, thereby suggesting that restoration and stress reduction could have a stronger mediation effect.

Studies categorizing greenspace type by intended purpose typically place urban greenspaces into three categories: parks, sports facilities, and natural greenspaces [Houlden, Porto de Albuquerque, Weich, and Jarvis 2021; R. Mitchell 2013; A. E. Van den Berg, Maas, Verheij, and Groenewegen 2010; Wood, Hooper, Foster, and Bull 2017]. Studies routinely acknowledge the particular benefits of each, i.e., that parks facilitate social interaction, sports facilities facilitate exercise, and natural greenspaces stimulate feelings of biophilia, although crossover is also acknowledged. Despite a consensus amongst papers that time spent in, or proximity to, all three of types of greenspace improves mental wellbeing, a consensus is rarely drawn with which type shows the strongest correlation with positive mental wellbeing. These differences could be put down to other contextual mediators, however, such as varying cultural preferences for what is considered the most pleasurable or relaxing use of leisurely time, differing quality of each type between locations, or the variation in methods used across studies. The lack of a consensus on the matter, however, reflects that all three of these common types have particular benefits in varying situations, and the prevailing consensus that all three types improve mental wellbeing supports the prevailing association between greenspace and mental wellbeing.

It has been suggested that just merely the presence of green space in urban environments is insufficient in improving mental wellbeing, however. Ha et al. found that the arrangement of green space in urban environments plays an important part in overall mental wellbeing benefits [Ha, Kim, and With 2022]. They reported that living near many smaller greenspaces rather than fewer, larger greenspaces resulted in lower psychological distress levels. This could seem counterintuitive, especially on the basis that greenspaces encourage physical activity, which is especially true for larger greenspaces. This being said, walking through or by several smaller greenspaces on a routine walk could provide particular benefits, and aligns well with the positive mental wellbeing effects shown in the presence of street foliage. A walk through a larger greenspace may require intentionality, rather than something that individuals are participating in just because its there, so more people are likely to see more benefits from the presence of smaller greenspaces that may just be, for example, on their way to work.

Foliage lined streets are another common type of urban greenspace, and have been shown to improve mental wellbeing by various studies [Barnes, Donahue, Keeler, Shorb, Mohtadi, and Shelby 2019; Sjerp De Vries, Van Dillen, Groenewegen, and Spreeuwenberg 2013; M. Van den Berg, Wendel-Vos, Poppel, Kemper, Mechelen, and Maas 2015; White, Alcock, Wheeler, and Depledge 2013]. One paper of note studied the relationship between the distance of streets trees from participants homes and antidepressant prescriptions, and showed that for individuals living within 100m of high density street tress, there was a lower rate of antidepressant prescriptions [Marselle, Bowler, Watzema, Eichenberg, Kirsten, and Bonn 2020]. While they also considered this for distances of 300, 500, and 1000m, there was no association; they suggest that this shows that unintentional contact with street foliage reduces the risk of depression.

3.2 Methodological Literature Review

3.2.1 Mental Wellbeing Questionnaires

A 2021 review of psychological assessments used within research concerning natural environments by Yao et al. showed that Restorative Outcome Scale (ROS), Profile of Mood States (POMS), Semantic Differential Method (SDM), Positive and Negative Affect Schedule (PANAS), and, Spielberger State-Trait Anxiety Inventory (STAI) were the most commonly used assessments [Wang, Helbich, Y. Yao, J. Zhang, P. Liu, Yuan, and Y. Liu 2019; W. Yao, X. Zhang, and Gong 2021]). For the purposes of this section, each method will be reviewed in sequence.

The Restorative Outcome Scale (ROS) is a self-reported scale that measures restoration in natural environments and measures relaxation and calmness, attention restoration, and cleaning one's thoughts, and can be expanded to measure subjective vitality and self-confidence also [Han 2018; Kalevi M Korpela, M. Ylén, Tyrväinen, and Silvennoinen 2008; Kalevi Mikael Korpela and M. P. Ylén 2009]. It functions to explore both primary theories of recovery, ART and SRT, something only itself and Restoration Scale (RS) achieve amongst other scales measuring restoration, although in comparison to RS, ROS performs worse on psychometric tests and has not been as widely examined [Han 2018]. RS, however, is not appropriate for use as a mental wellbeing assessment, as it determines restorative qualities in the environment [Han 2003], whereas ROS measures the outcome of restoration on mental wellbeing [Kalevi M Korpela, M. Ylén, Tyrväinen, and Silvennoinen 2008; Kalevi Mikael Korpela and M. P. Ylén 2009]

The Profile of Mood States (POMS) is a psychological rating scale used to assess transient, distinct mood states and was developed in 1971 [Pollock, Cho, Reker, and Volavka 1979]. It is lauded for its simplicity to administer and understand by respondents, and measures six different dimensions of mood over a period of time, which include tension, vigor, fatigue, depression, and confusion [Arruda, Stern, and Somerville 1999]. It uses a five-point scale from "not at all" to "extremely", and has two forms, a long form designed for adults that consists of 65 items, and a short form designed for adolescents that consists of 37 items.

The Semantic Differential Method (SDM) is a rating scale based upon Charles Osgood's theory of the semantic differential , and involves presenting study participants with bipolar pairs of adjectives and asking them to place their position on a matter between the two adjectives [Osgood, Suci, and Tannenbaum 1957]. SDM has been widely used both in academic research, but also in market research, thanks to its simplicity and versatility. It is straightforward for participants to understand, but can also give a diverse understanding of attitudes towards a particular matter if adjective pairs are selected thoughtfully and appropriately. A good example of its use in the relationship between greenbathing and mental wellbeing is a study of the psychological and physiological effects of autumnal walks through parks that used the bipolar adjective pairs "comfortable to uncomfortable", "natural to artificial", and "relaxed to awakening" [Song, Ikei, Igarashi, Takagaki, and Miyazaki 2015]. The pairs used here reflect several different measures, and although not specifically related to traditional measures of wellbeing, were used in combination with POMS scores which uses more traditional measures.

The Positive and Negative Affect Schedule (PANAS) is a psychological tool intended to assess an individual's overall mental wellbeing, and is based on the key principles of emotional dimensionality, self-reporting, mood assessment, scalability, and linguistic and cultural adaptability [Barrows, Thomas, and Van Gordon 2021]. These principles make it a diverse research tool that is applicable to a variety of purposes. It consists of two subscales, the Positive Affect (PA) and Negative Affect (NA) scales, which use a 5-point likert scale. It has been widely used in community contexts, and is respected as a reliable tool for assessing an individual's positive and negative emotions, and for this reason, is the most extensively used scale for assessing positive and negative emotions [Díaz-García, González-Robles, Mor, Mira, Quero, García-Palacios, Baños, and Botella 2020].

The State-Trait Anxiety Inventory (STAI) is a psychological inventory that is based on a 4-point likert scale and consists of 40 questions [Spielberger 1983]. It measures two types of anxiety, State Anxiety (S-Anxiety), which determines anxiety about a particular event, and Trait Anxiety (T-Anxiety), which reflect anxiety level as a personal characteristic. In other words, S-Anxiety determines the current state of anxiety of a respondent, whilst T-Anxiety evaluates how prone a respondent is to anxiety. It is widely used as it is both reliable, and also differentiates well and accounts for how a particular matter impacts both State and Trait anxiety, as a singular measure [Spielberger 1983].

3.2.2 Image Analysis

One method of image analysis taken in this area is in the identification of greenspace pixels, or put simply, by identifying how much green is present in the image. For their study of greenspace exposures in Irish cities, O'Regan et al. used existing Python scripts to identify objects within imagery, and subsequently identified how green these objects were, using this information to build an idea of how green each image was [O'Regan, R. F. Hunter, and Nyhan 2021]. More commonly, however, a machine learning based computer vision approach is typically taken thanks to recent improvements in machine learning technology, making it more accessible to a wider range of researchers. This has been applied in a variety of ways, with many studies using existing computer vision technologies, whereas others modify existing technologies in order to achieve a specific outcome more relevant to their individual studies. An example of the latter is the use of the Pyramid Scene Parsing Network (PSPNet) semantic segmentation model in order to identify tree lines in street imagery in a study seeking to understand the spatial distribution of street tree canopies [Cai, X. Li, Seiferling, and Ratti 2018; Stubbings, Peskett, Rowe, and Arribas-Bel 2019].

In terms of the use of existing computer vision technologies, three frontrunners are identified: Azure Computer Vision, Clarifai, and Google Cloud Vision [Ghermandi, Depietri, and Sinclair 2022]. Google Cloud Vision is the most commonly used, a comparative study of the three identifying 7 studies using it, with only 3 using Clarifai, and 1 using Azure Computer Vision [Ghermandi, Depietri, and Sinclair 2022]. All three provide users with a series of tags per image, representing what the model identifies in the image above a certain significance level. This comparative study found that Google Cloud Vision and Azure Computer Vision returned on average fewer tags than Clarifai, however, the total number of possible tags was shown to be highest in Google Cloud Vision. This study concludes that whilst these existing technologies work sufficiently for the time being, future studies should use multiple techniques in order to verify the efficacy of utilised Computer Vision technologies.

3.2.3 Location Analysis

Two primary methods for determining greenness of location data are used. The first of these methods is to identify the proportion of greenspace in comparison to total area within a specified distance of a location [Mears and Brindley 2019; Triguero-Mas, Dadvand, Cirach, Martínez, Medina, Mompart, Basagaña, Gražulevičienė, and Nieuwenhuijsen 2015; Wüstemann, Kalisch, and Kolbe 2017]. This involves the use of either satellite imagery to identify greenness, or existing GIS data that identifies greenspaces. Defining the boundaries within which greenness is analysed also takes two avenues, depending on what the study is attempting to identify.A buffer zone is typically drawn in the form of a radius around a given location point is drawn, at a radius of the researchers discretion.

The second of these methods is to identify the visibility of greenspaces around a given location point [Brinkmann, Kremer, and Walker 2022; Labib, Huck, and Lindley 2021]. This also uses satellite imagery or GIS data for the identification of greenspaces, but combines this with satellite depth information to assess whether greenspaces surrounding a given point can actually see greenspaces. The buffer zone in this circumstance is effectively defined by the objects that an individual standing a particular location wouldn't be able to see past. This method has been explored by a variety of studies that typically argue that this gives a better measure of greenness by suggesting that the visibility of greenness is what mediates the influence of greenspaces on human responses.

3.3 Research Gaps

Whilst this is a well researched field that has explored many facets of this relationship, there are several clear research gaps that are yet to be addressed.

1. It has been suggested by a variety of papers that factors determining the quality of greenspaces, such as biodiversity and maintenance, should be investigated further in order to better understand if they have independent influences on greenbathing and mental wellbeing[Bratman, Olvera-Alvarez, and Gross 2021; Krekel, Kolbe, and Wüstemann 2016; Nutsford, Pearson, and Kingham 2013].

2. One paper by Triguero-Mas et al. suggests there could be some significance of greenness surrounding work and study spaces in terms of how greenbathing impacts mental wellbeing [Triguero-Mas, Dadvand, Cirach, Martínez, Medina, Mompart, Basagaña, Gražulevičienė, and Nieuwenhuijsen 2015].

3. Another study by Nutsford et al. identifies a distinction between active and passive usage of greenspaces, proposing that further research using a wider variety of techniques should be undertaken to better understand how these individually effect the relationship between greenbathing and mental wellbeing. [Nutsford, Pearson, and Kingham 2013].

4. Multiple papers have identified that the understanding of the mechanisms of the effect that age and gender have on the relationship between greenbathing and mental wellbeing is limited, suggesting that more complex techniques using machine learning models be used to better understand this relationship [Sang, Knez, Gunnarsson, and Hedblom 2016; Sillman, Rigolon, Browning, McAnirlin, et al. 2022].

4 Methodology

4.1 Research Questions

Given the literature and identified research gaps, this paper aims to address these questions:

1. Is there an association between being amongst greenness and mental wellbeing?
2. How does gender mediate the relationship between being amongst greenness and mental wellbeing?
3. How does the greenness of an individual's workplace mediate the relationship between being amongst greenness and mental wellbeing?

In terms of contribution to the existing literature, these research goals are thought out to address the following. The first research goal seeks to affirm the validity of EMA as a research method in this area, subsequently affirming the significance of the additional research goals; does this study find similar results to existing literature? The second research goal attempts to investigate the relationship between gender and greenspace walking in terms of mental wellbeing, in order to see if new insights can be drawn on this particular relationship, with men being shown typically to experience the strongest impact of this relationship. The third and final research goal seeks to address a prevailing research gap, in that existing research consistently focuses on greenness around an individuals home rather than around their workplace.

4.2 Introduction to Methodology

To address the identified research gaps, and thus fulfil the primary and secondary research questions of this work, does EMA produce results consistent with existing findings in the study of the relationship between greenspace walking and mental wellbeing, and can EMA fill existing research gaps in the study of the relationship between greenspace walking and mental wellbeing. The method for this study was based on the 'DIY EMA' system produced by Jon Bird et al., and this was used to prototype the intial EMA system. This uses Twilio to send and receive WhatsApp messages for the EMA system, with a bespoke server and conversation handler developed in Java to schedule messages, process images, collect data, and handle data.

4.3 Study Design

As is inherent with EMA, the study was longitudinal, with participation occurring repeatedly over the course of a week, and observational, as results were viewed and data was collected without intervention. To avoid as much intervention as possible, participants were not primed or guided towards participation in particular environments, assuming that if participants participated regularly throughout the week, they would experience a diverse range of environments of differing greenness. Participation was limited to UK residents, in line with analysis of sunrise and sunset data. The study took place over the course of a week, which allowed for repeated participation and therefore a larger dataset from which to analyse the collected data. Due to the scope of the project, and the need to develop further software for location analysis, the time frame was kept to a week.

A link to a participant information website was sent out to prospective participants so that they were able to understand the study fully and make an informed decision on their participation. The sheet also included instructions of the self-onboarding process. The link to the participant information website was sent primarily to those in the Bristol area, but participants were asked to forward the website on to anybody else who they believed would be happy to engage with the study. If participants decide to participate, they onboard themselves by first associating their telephone number with the Twilio chatbot, and then completing a couple of onboarding questions, designed to help understand the identified research gaps. Upon completing the onboarding process, participants are informed of the instruction they need to provide to the chat bot to commence a walk, and are then able to participate in any number of walks they please. During the walking period, the EMA beings a new questionnaire every five minutes, including one at the beginning of their walk. This gives a significant number of data points throughout a walk of reasonable duration, but also means that participants are not over-encumbered by the EMA, and are allowed time to enjoy their walk such that their responses may differ throughout.

Participants were only allowed to end their current walk during a period of waiting, such that complete data points for each questionnaire were acquired. Furthermore, participants were asked not to participate if for any reason they wouldn't be able to send photographs on their walk, which ensured that an image greenness score could be acquired. These both ensure that the correct data is being collected throughout the walk, and although participants were given the opportunity to end a walk before it had taken its course, in most cases, this would still provide sufficient data. Participants were incentivised to participate by providing them with a composite image including all the photographs taken during the duration of their walk, as well an overlayed graph showing how their emotional wellbeing changed throughout their walk, which is shown in Figure 7. In the participant information sheet, participants were given participation advice to ensure their safety. This included a reminder for participants to only interact with the EMA when it was safe to do so, e.g., not whilst they're crossing a road, and also included a warning about interacting with the system at night, and to always consider personal safety.

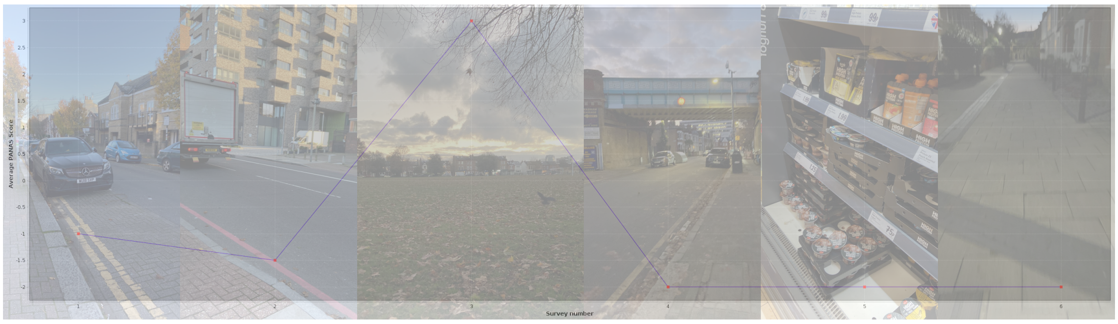

Figure 4.1: An Example of a Composite Image Given to Users

4.4 WhatsApp Chatbot Description

The WhatsApp chatbot was developed using Java, and utilises the Twilio API to send and receive WhatsApp messages. The functionality of the chatbot included handling the onboarding of participants, administering surveys, and processing image data. This approach to EMA made the most of the ubiquity of WhatsApp, which reduced barriers to participation. The chatbot was able to handle several users simultaneously, providing the scalability needed for an EMA system. Furthermore, the efficient analysis of image data through the Google Vision API meant that much of the data processing code could occur as the program collected data. The chatbot was designed to be as user friendly as possible, so a help option was included, and responses required only the input of numbers, as not to interfere too much with walking.

4.5 Data Collection Procedures

Participant information data was collected during the onboarding process, including the participant's gender and the location of their workplace; these address the identified research gaps. During walks, participants answer four questions relating to their mental well-being. For this, I used a modified version of PANAS. There were several factors supporting the rationale for using PANAS. The first of these is that it is self-reported scale, which is a necessity for EMA research. The second is its scalability, which ensures efficiency in terms of data analysis and also the flexibility of the questionnaire, the benefits of which are discussed shortly. The third factor is its reliability, which is reflected well by the fact that it is the most widely used assessment for positive and negative emotions.

Once participants responded to these questions, they were asked to send a picture that best shows their surrounding environment, and subsequently, to send their location. Images served a two-fold purpose, to be able to create the composite image to send back as a participation incentive, but also for greenness analysis. Location data was retrieved to assist in providing a more well-rounded greenness rating and to help assess the quality of greenspace.

4.6 Variables and Measures

PANAS consists of reflective or retrospective questions that are asked after a participant has engaged in the activity in question, which of course, is not appropriate for EMA. Furthermore, the standard PANAS uses two 10-question scales, one for positive affect and one for negative affect, which is also not appropriate for EMA, as it would be too time-consuming and may in itself impact the emotions that this study is aiming to measure.

Due to these factors, I modified PANAS to incorporate only two questions for positive affect and two for negative affect. Likewise, the PANAS questions were modified such that they asked the participant for their responses in the moment. Below are the four questions I selected:

1. How content do you feel at this moment?
2. How relaxed do you feel at this moment?
3. How anxious or worried do you feel at this moment?
4. How irritated or frustrated do you feel at this moment?

These items were carefully selected to try and best represent a participant's overall emotions, and in a way that was balanced between positive and negative affect. Moreover, these questions reflect stress related emotions better than the other questions in the default PANAS survey, accounting for stress as a primary mediating factor in the relationship between time spent in greenspaces and mental wellbeing.

Each image was fed into Google's Cloud Vision API for object detection and classification, which gives back a list of labels corresponding to what it detects in the image, and a confidence rating. A score from 0 to 1 was calculated using these labels, increasing the score if more labels reflective of greenspace were present. Using a list available to developers using the API, all labels determined to represent greenspace were identified. If none of these labels were present, the image received a greenness score of 0, but for every label present, the score was incremented as a proportion of that label to the total number of labels returned. Since it only provides labels for images that it perceives it has a high confidence rating for, this rating was ignored.

Whilst image data was analysed throughout the walks, and was integrated into the conversation handler and server, the location data was analysed separately. This was done as the analysis of location points was costly and would slow the program down, which wasn't a problem with the image analysis as the images were sent to Google Cloud

Vision for analysis. Location analysis took place in a separate program written in Python. Using Geopandas, the OS Open Greenspace map showing urban and rural greenspaces was read into the program and used for analysis. The score was calculated by drawing a 300m buffer around location points read into the program, and determined the proportion of greenspace area to the total area of the buffer. This is consistent with the methods used by Triguero-Mas et al. in their paper investigating how different approaches show a positive association between greenbathing and mental wellbeing

4.7 Data Analysis

A Spearman's correlation was used to assess the strength and direction of the association between both image greenness scores and location greenness scores with PANAS scores, which addresses research question 1. A Spearman's correlation was also used between genders to assess their relationships with image greenness, location greenness, and PANAS scores, to set up a subsequent Fisher's Z Transformation for the comparison of the strength of the correlation between both image greenness scores and location greenness scores with PANAS scores between genders. An Ordinary Least Squares regression analysis was used to model the relationship between both image and location greenness scores and PANAS scores in relation to workplace greenness scores. Finally, a time series analysis was used to analyse trends in PANAS scores over time, in order to provide insights in terms of walking interacting with PANAS score trends, subsequently conducting time series analysis with both image and location greenness scores to assess whether any statistically significant trends in PANAS scores could be attributed to greenness or if they were likely caused by other external factors.

4.8 Pilot Testing

Prior to launch, multiple pilot tests were launched. The initial pilot test, which was conducted within, but towards the end of the development stage, aimed to check for problems with message scheduling, and the phrasing of the questions used in the EMA. This initial pilot test showed that there were significant problems with message scheduling following a waiting period, and also highlighted that the original phrasing of the image prompt, which asked participants to take a picture of an object in their surroundings that best described their feelings, failed to capture the environment accurately. Following this, message scheduling problems were resolved, and the image prompt was changed to ask users to take a picture that best showed the environment that they were in.

A second pilot test was conducted once the program was completed, and was designed to test if the program would hold up when multiple participants interacted with it concurrently. This test involved three participants interacting with the system at once, and was intended to last an hour, but issues concerning the Twilio API's message scheduling and delivery arose. After implementing additional code to combat these issues, a final pilot test was conducted under the same conditions as the second. This test ran smoothly over the duration of the hour, and signalled that the system was ready for deployment.

4.9 Quality Control

The study was conducted over a single week to minimize participant fatigue and ensure high data quality. This timeframe was chosen deliberately to limit the intrusion into participants' daily lives and enable them to continue to enjoy their walks; maintaining a brief yet effective study period enhanced the ability to collect genuine responses without altering a participant's typical behaviour.

To ensure comprehensive data collection, participants were only able to end their walks during a waiting period and were asked only to participate if they were able to take images for the duration of the walk. Furthermore, offering the image incentive to participants ensured that they continued to participate by making participation an enjoyable experience. This also helped to reduce participant fatigue and increase satisfaction, which improved the data quality. Once the EMA system was deployed, continuous checks took place to ensure that data was being collected properly and that messages were being scheduled correctly. This involved dummy participation to check that everything was happening at the right time, and that waits were being scheduled and handled correctly.

4.10 Ethical Considerations

During the planning and execution of this study, several ethical considerations were addressed. Ensuring informed consent by supplying sufficient information about the study was key to this, and participants were given a comprehensive overview of what the study was observing, alongside how their data was handled. Furthermore, the ability of participants to withdraw at any stage was emphasised. This participant information form also emphasised the importance of safety in participation in this study, suggesting that participants consider their participation during nighttime. In terms of privacy and data security, measures were put in place to anonymise data as best as possible, although participant telephone numbers were kept in a participant information spreadsheet such that the program could identify participants even if it halted. These telephone numbers were deleted upon cessation of the study, such that they were never viewed. Data was kept securely in the EC2 instance, and transferred securely to a single personal device. Data was stored in a password protected folder on this device.

4.11 Limitations

The study had several limitations. Its one-week duration, although beneficial for minimising participant fatigue, limited the scope for observing longer-term behavioural patterns and changes in mental wellbeing. The reliance on self-reported data could introduce subjective biases. Additionally, the exclusive focus on UK residents and the specific urban settings may limit the generalisability of the findings to other geographical and cultural contexts. Technical limitations, particularly in image and location data analysis, could also have influenced the accuracy and comprehensiveness of the environmental assessments.

5 Implementation

5.1 System Overview

Whilst Twilio provides Twilio Studio, a flowchart-based system that uses pre-defined functions and user creatable functions written in JavaScript, the development of a purpose-built conversation handler for the EMA system written in Java was decided as the best course of action. The DIY EMA system provided by Jon Bird et al uses Microsoft Power Automate in conjunction with Twilio Studio workflows in order to give seamless recording of EMA data, however, the flexibility and total control offered by writing a bespoke program for this purpose gave better control over how messages where scheduled, and gave a baseline platform upon which further EMA systems could be based. Furthermore, the integration of image processing code and statical analysis into the conversation handling saved the need for creating bespoke code to join a Twilio Studio flow, instead allowing a seamless handling of data processing and collection throughout the study.

5.2 Data Collection and Processing Mechanism

Initially, the data collection program uses the Twilio API to listen for incoming messages. Once it receives an inbound message, it listens to see if it is receiving a 'start walk' message, or if they are a new user. The associated logic routes to an onboarding process if it's the participants first time. If so, it creates a NewUserConversationHandler object, which handles new user logic, and starts the onboarding process, asking for participant gender and the location of their workplace. If the message received is from a participant who has passed the onboarding process, it creates a SurveyConversationHandler object, and starts the survey logic, conducting the typical survey.

The standard survey class collects the information from each participant for each 5 minute survey, placing them in a survey response object, and collects these responses. Once a walk is completed and all the data is collected, a new excel spreadsheet is created and the data appended if this is their first walk, and if not, it is appended to their existing spreadsheet. During this process, it processes the images for the greenness score also, passing the images to the Google Vision API for analysis. Data in this spreadsheet is completely anonymised, with the participants being assigned a unique participant number during the onboarding process, although their phone number is present in the participantinformation spreadsheet such that the system functioned if it needed to reboot.

At the point of each survey, a list of paths guiding to where each individual image was stored was collected. At the cessation of a walk, these images were stitched together and the PANAS scores were placed on a graph using JFree chart, showing how the mental wellbeing of each participant changed throughout each walk. This chart was overlaid on the stitched images, showing a complete image of the pictures they took throughout the walk alongside their data. This final image was hosted on an AWS S3 Bucket, so that the Twilio API had a webhook URL from which to send the image to the participant.

In conjunction with the primary program associated with the data collection process, a second program was developed for the analysis of location points to achieve a greenness score. This was developed separately due to the timeframe concerned with the development process and the need to collect data promptly. By isolating it, it means that analysing the data required an additional step once all the participant data was collected. However, processing the data from these location points would have added additional strain to the program, potentially creating delays and introducing latency for participants who may be carrying out a walk concurrently. Image data was processed during the walks since it allowed images to be deleted after analysis, significantly reducing the storage needs of the AWS EC2 instance the program was hosted on. Furthermore, images required processing for the image that is returned to the user following their walk, so all image data was analysed at this point.

The location analysis program takes in the users location points for each data point and uses an OS map showing polygons that refer to the location of green spaces, and ascertains whether the participant was in a green space at that point, and if not, how close they were to green spaces within a mile radius. This gave a green score ranging from 0 to 1 for each data point. This program also conducted all the statistical analyses for the PANAS scores and greenness scores for each participant, providing a complete data package with a variety of analyses to study the aforementioned research gaps, and also to focus on the core study of the relationship between greenspace walking and mental wellbeing.

5.3 Technical Issues

The second pilot study, as mentioned in the methodology section, highlighted an issue with concurrency. The Twilio API restricts your individual number to a requests per second (RPS) rate limit of 1, which with multiple concurrent participants, meant that the program could seize up and not send a participant the message they were scheduled to receive. Referring to the Twilio API documentation, the solution of utilising an exponential back off and retry was implemented. This code checks to see if the Twilio API error has been thrown, and if so, waits a second to send the message, if the message couldn't be sent, it then tries again at two seconds, and exponentially multiplies the duration of each wait until it's attempted x times.

6 Results

6.1 Dataset Consideration

Of 10 participants who completed the onboarding process, 7 recorded data from a walk, and of those 7 participants, only 6 contributed appropriate data. Of those 6 participants, 3 identified as male, and 3 identified as female. 19 walks were recorded in total, providing 58 individual data points.

6.2 Overall Association Between Greenness and PANAS Scores

6.2.1 Image Greenness Score and PANAS Score

Spearman Correlation = 0.41, p-value = 0.001, < 0.05

Analysis showed a significant positive correlation, indicating that a higher image greenness score is associated with better mental wellbeing.

This is consistent with the expected result.

6.2.2 Location Greenness Score and PANAS Score

Spearman Correlation = 0.33, p-value = 0.012, < 0.05

Analysis showed a moderate positive correlation, indicating that a higher location greenness score was somewhat associated with better mental wellbeing.

This is consistent with the expected result.

6.3 Influence of Gender on the Effect of Greenness on PANAS Scores

6.3.1 Image Greenness Score and PANAS Score

z-score = -2.173, p-value = 0.029, < 0.05

Analysis showed that there was a statistically significant difference in the effect of image greenness scores on mental wellbeing, with the effect stronger in females.

Although there was a statistically significant difference, the expected result was that the effect would be stronger in males, so this is inconsistent with the expected result.

6.3.2 Location Greenness Score and PANAS Score

z-score = -1.900, p-value = 0.057

Analysis showed that there was no statistically significant difference in the effect of location greenness scores on mental wellbeing, although the effect was stronger for females.

The p value is close to significant (< 0.05), however, the significant result would have reflected that the effect was stronger in females, so this is inconsistent with the expected result.

6.4 Influence of Workplace Greenness on PANAS Scores

6.4.1 Image Greenness Score and PANAS Score

Interaction Term Coefficient = -7.376, p-value = 0.016, < 0.05

Analysis showed that workplace greenness had a significant influence on the relationship between image greenness score and PANAS score.

The negative interaction term coefficient indicates that a lower workplace greenness score intensifies this effect.

This is consistent with the expected result.

6.4.2 Location Greenness Score and PANAS Score

Interaction Term Coefficient = -9.747, p-value = 0.007, < 0.05

Analysis showed that workplace greenness had a significant influence on the relationship between location greenness score and PANAS score.

The negative interaction term coefficient indicates that a lower workplace greenness score intensifies this effect.

This is consistent with the expected result.

6.5 Trends Throughout Walks by Participant

During the analysis of average PANAS scores throughout the duration of walks, only three walks showed a statistically significant trend. All three trends were positive, so, average PANAS score increased throughout the walks. This was discovered in participant 2's 4^{th} walk, participant 7's 3^{rd} walk, and participant 9's 1^{st} walk. Since this was discovered in only one of each of those participant's walks, it is assumed that this is not reflective of each participant's general response to walking in terms of mental wellbeing, although, this is the only walk participant 9 recorded.

6.5.1 Participant 2, Walk 4

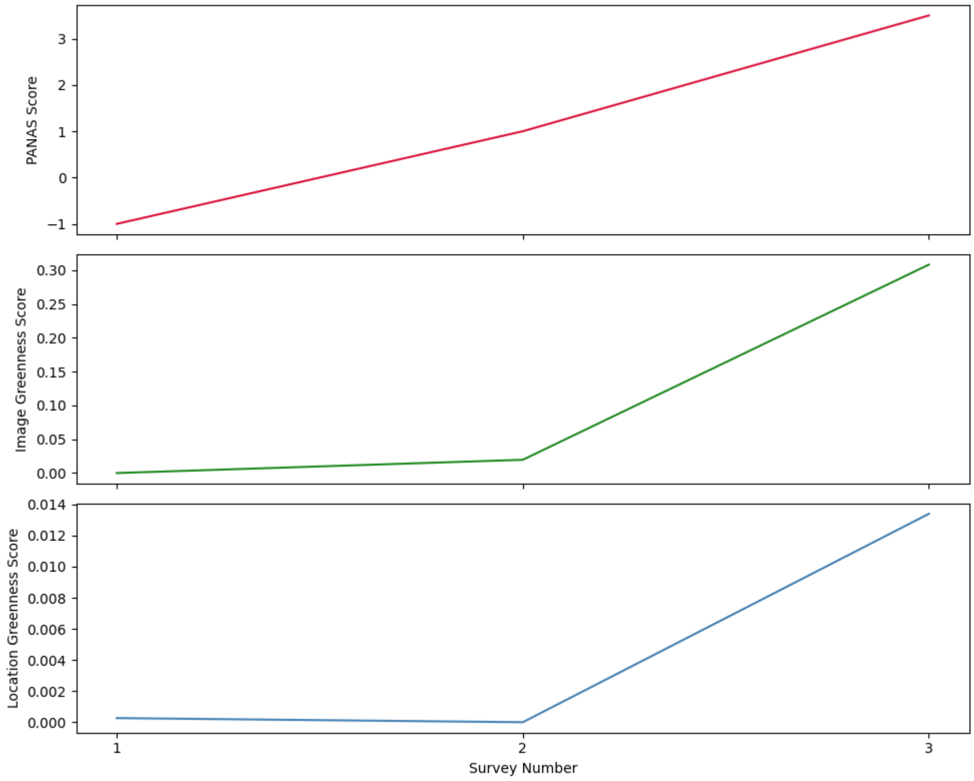

Figure 6.1: Trends of PANAS and Greenness Scores During Participant 2's 4th walk

Participant 2's 4th walk shows that PANAS score increases throughout the duration of the walk, alongside both the image greenness score and location greenness score, with image greenness score in particular showing a very similar trend to the increase in PANAS score. Since both greenness scores showed a similar positive trend, it can be assumed that the positive trend in terms of PANAS score can be attributed to increased greenness, particularly considering that this walk was the only statistically significant walk in terms of PANAS score throughout the duration of a walk.

6.5.2 Participant 7, Walk 3

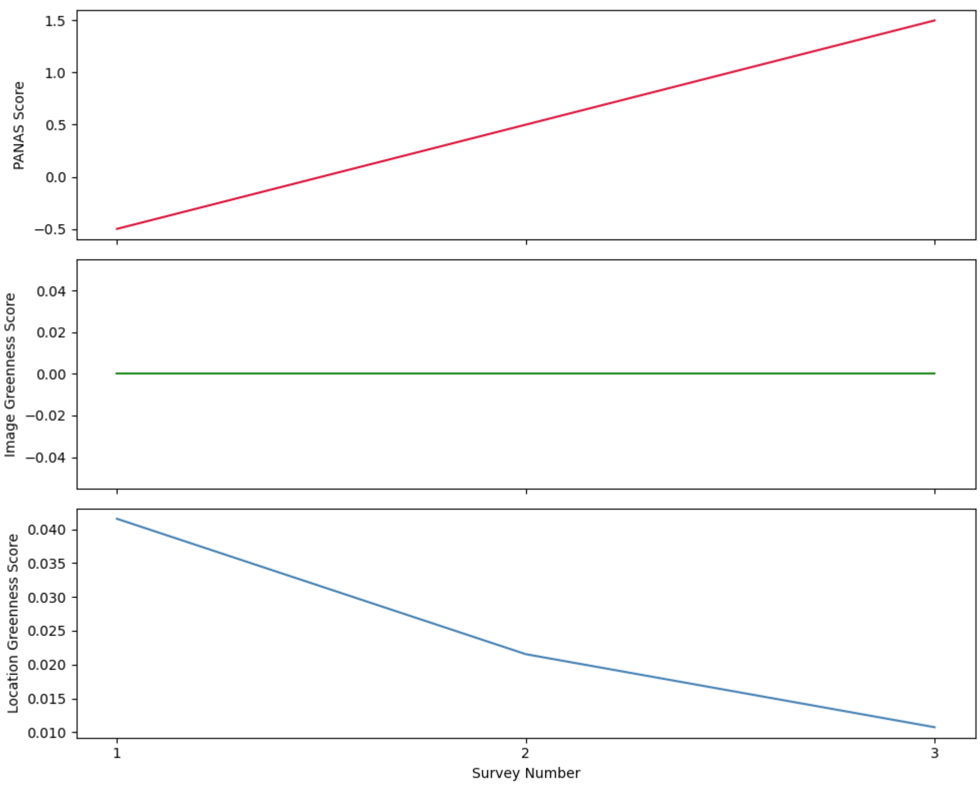

Figure 6.2: Trends of PANAS and Greenness Scores During Participant 7's 3rd walk

Participant 7's 3rd, walk shows that whilst PANAS score increased throughout the walk, the image greenness score showed no trend, getting a score of 0 at each point, and the location greenness score decreases throughout the walk. This is the inverse of what was expected, however, a low image greenness score could indicate that regardless of the presence of greenness within a 300m radius (as is indicated by a non-0 location greenness score), these greenspaces were completely obstructed by buildings, such they weren't visible by the participant. The increase of PANAS score throughout the walk could also be reflective of other influences.

6.5.3 Participant 9, Walk 1

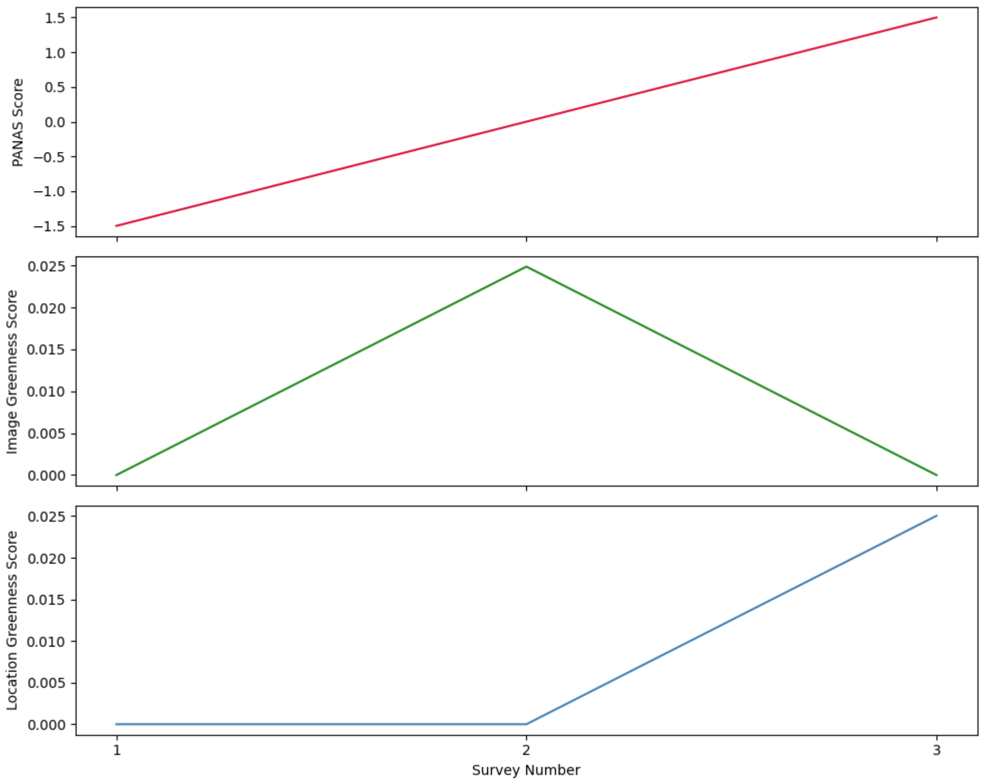

Figure 6.3: Trends of PANAS and Greenness Scores During Participant 9's 1^{st} walk

Participant 9's 1^{st} walk shows that whilst PANAS score increased throughout the walk, the image greenness score showed no trend, although the location greenness score showed a positive trend. Although location greenness score explains the positive trend in PANAS score, it is worth noting that image greenness score is more reflective of how green the participants surrounding environment is in that instance. Furthermore, it is necessary to consider that the image greenness score is either 0 or very low. It is possible in this case , then, that the increase in PANAS score is explained by other external factors.

7 Discussion

7.1 Is there an association between being amongst greenness and mental wellbeing?

The results showed that there was a significant association for both image greenness and location greenness with mental wellbeing, although it is important to take into consideration the limited sample size in drawing conclusions from this. This being said, however, the multifaceted approach of using both image greenness and location greenness substantiates these claims. This result was consistent with the literature discussed prior, so particular goal associated with this research question was achieved. This result reinforces the validity of EMA as a research tool in this area, and subsequently, the validity of the other findings in this study.

The stronger association between mental wellbeing with image greenness rather than location greenness indicates a few things. Given how image greenness was calculated, as in, that it was more of a measure of the overall greenness of the general area around a given location, rather than a measure of greenness visibility, the findings indicate that it is possible that the greenness of an individual's immediate surroundings impact their mental wellbeing more significantly than the general greenness of the area they're in. It also indicates that the quality of what is identified as a greenspace could be more considerable in terms of this effect, rather than the quantity; many parks which contain little foliage within a certain distance would give a high location greenness score, when actually the impact of those parks on mental wellbeing and to the sense of greenness of the surrounding areas is reduced, due to a lower quality. It is also worth noting that imagery reflects a qualitative measure of greenness, as participants actively engage and respond to the prompt based on their own perception, rather than location, which could be considered a more objective measure, although the classification of spaces as greenspaces is arguably subjective. This difference indicates a personal reflection on the interpretation of the prompt, which could change based on a variety of factors, including age, nationality, and other socioeconomic factors.

7.1.1 Future Work

The goal of this objective was to validate EMA as a tool in this field of study, and significant results for both image and location greenness scores affirms this, as such, no future work is indicated for this area.

7.2 How does gender mediate the association between being amongst greenness and mental wellbeing?

The findings showed that gender had a statistically significant effect on the impact of image greenness on mental wellbeing, and a near statistically significant effect on the impact of location greenness on mental wellbeing. For both measures it was found that the effect was stronger within participants who identified as female, which contradicts the existing findings which suggest that this effect is stronger in men. Given the scale of this study, insufficient representation of a variety of groups could lead to these findings actually indicating some other trend amongst female participants and male participants, rather than this association being able to be reduced down to purely gender.

Differences in significance between image greenness and location greenness could indicate a difference in the way that women interpreted the image prompt in comparison to men. It is possible that female participants considered the greenness of their surroundings more so than male participants, which could be reflective of more active engagement or a deeper connection with the environment in female participants, although again, this could be due to other external factors. Given the context of an EMA study, which considers particular benefits such as ecological validity and limited recall bias, it is possible that existing techniques used to analyse this relationship failed to recognise how this effect functions in the every day life of participants, or possibly whether there is a difference in recall bias between genders.

7.2.1 Future Work

Whilst this portion of the study attempted to address the identified gap in the literature, a more nuanced approach considering more specific components of gender identity should be taken.

7.3 How does the greenness of an individual's workplace mediate the association between being amongst greenness and mental wellbeing?

The results showed that workplace greenness had a statistically significant effect on the impact of both image and location greenness on mental wellbeing, with a lower workplace greenness score having a stronger effect. This indicates that those who work in locations that are less green are more responsive to greenness in other areas outside of their workplace. This could be explained by the concept of environmental compensation, which suggests that individuals experiencing a deficient experience of a given environment are more likely to place greater value on experiencing that environment when they do.

Another reason for this could be the contrast effect, which suggests that for participants who spend their days working in less green surroundings, greenness in other contexts might present itself as a more impactful contrast, therefore having a more significant impact on their mental wellbeing. There are two primary conclusions that can be drawn from this finding, which are as follows. The first of these is that it is possible that individuals who work in less green areas experience lower mental wellbeing generally, or at least when they are at work. The second is that there could be a broader need for balance in terms of environment.

7.3.1 Future Work

Based on these finding, future studies should look more at specific aspects of the workplace in relation to greenness that may impact this relationship. For example, studies could understand the impact of workplace stress as mediator in this relationship, or could also focus on the visibility of greenness from workplaces, rather than a measure of general greenness.

7.4 The Use of EMA as a Research Tool in the Study of the Relationship between Time Spent in Greenspaces and Mental Wellbeing

Whilst the development of the EMA program was successful, and there were no issues reported throughout the duration of the study, there are some considerations to be made.

7.4.1 Future Work

Expand on the Java software developed for this study such that it is more accessible for researchers unfamiliar with programming. This could be achieved through the implementation of a GUI and a standardised plaintext input format that could be parsed to modify the functionality of the program.

7.5 Summary

Whilst this study provided a novel insight to this field in terms of workplace greenness interaction, the limited dataset restricts any significant conclusions being drawn from the collected data. This being said, although the evidence is limited, it may not be the case that a larger dataset would alter the statistical significance of these findings, and as such, further studies understanding, in particular, workplace greenness interaction should be undertaken in order to validate the claims made in this study, and to better understand how and why this relationship occurs.

8 Conclusion

This project provided meaningful insights in terms of the use of EMA in this field of study, by showing results consistent with those found in literature. Furthermore, a contribution to the literature was made in terms of the discovery of an association between workplace greenness and the relationship at hand. A methodological contribution was made in the development of a Java based EMA system which can be modified for use in different EMA studies.

A longer term study with more participants would be beneficial in future, in order to increase the reliability of results. Equally, the Java EMA program could be modified to help provide further insights into workplace greenness and what mediates that effect. Future work could involve the expansion of this Java program as an all-inclusive EMA program with adaptable functionality. Equally, location analysis could take place within the same Java program.

The approach of using both image and location data, however, could be used in future work, in order to give a two-sided view of greenness, affirming findings, and indicating differences in how greenness is calculated. A similar study could be carried out, but could also use google street view imagery to assess greenness, which could prove straightforward given that location data was already acquired. Furthermore, asking participants to take a picture outside their workplace could give more consistency in the types of greenness data as a whole. Finally, more attention should be paid to the phrasing of the image prompt, as to guide participants more.

Appendix

EMA Study Help Sheet

Troubleshooting: Stopped Receiving Messages

If you find that you have stopped receiving messages from our system during a time when you are supposed to, please follow the steps below to troubleshoot the issue:

1. **Send Any Message:** Try sending any message repeatedly. This action can help in cases where the messaging system may experience backlogs.
2. **Check for Connectivity:** Ensure that your device has a stable internet connection, as this can affect message delivery.
3. **Restart the Chat:** As a last resort, you can type 'end' to exit the chat, and then type 'join probably-hide' to join again.
4. **Email for Assistance:** If you continue to face issues and do not receive messages, please email me directly for support at uu19561@bristol.ac.uk.

I apologise for any inconvenience this may cause and thank you for your patience and understanding.

For any further assistance or inquiries, feel free to reach out via the email provided above.

Figure 1: Help Sheet

Appendix

Welcome to the Study!

I am excited to invite you to participate in a study exploring how walking in green spaces impacts emotional well-being. This study utilises Ecological Momentary Assessment (EMA) to gather real-time data as you experience various environments.

Participation Overview

- **WhatsApp Integration:** To participate, please add the following number to your WhatsApp contacts: +1 (415) 523-8886. You can assign any name to this contact.
- **Joining the Study:** Send a message saying 'join probably-hide' to this number. Then, send 'start walk' to complete your onboarding.
- **Workplace Location:** On Android, press the file icon and choose location, then locate your workplace on the map, or search for it in the searchbar, and send. On iPhone, press the plus icon, then location, then locate your workplace on the map, or search for it in the searchbar, and send.
- **Starting a Walk:** Simply type 'start walk' to begin your walking session.
- **Internet Connectivity:** Try to participate only when you know you'll mostly have an active internet connection as this will be required in order to send and receive messages.
- **Taking Photographs:** If you cannot take a picture for any reason, please refrain from initiating a walk.
- **Participation:** If you are able to, your repeated participation would be greatly appreciated. By participating in multiple walks, you will contribute more to the dataset, and more meaningful insights could be extracted from your data.

During the Walk:

- **Surveys:** You'll receive a survey every 5 minutes, including one at the beginning of the walk. Try to answer these questions as truthfully as you can, answer exactly how you feel in the moment.
- **Photographs:** Take and send photographs of your surroundings when prompted. These images help us assess the greenness of your environment.
- **Location:** On Android, press the file icon and choose location, you should see an option for your current location, tap that and send. On iPhone, press the plus icon, then location, then tap on the blue dot and tap on the 'My Location' label to send your location.
- **Ending a Walk:** You can end your walk during any 5-minute wait by sending 'end walk', however, if you're in the middle of a survey, please complete it before ending the walk.
- **Walking at Night:** Participation is still valuable even during nighttime walks due to the way images are analysed, however, please consider the safety of doing so prior to participation.

Data Use and Security

- **Images:** The photographs you send are used to analyse the greenness of your surroundings. They are securely processed and deleted immediately after processing.
- **Location Data:** Your location coordinates are anonymised and used to evaluate the quality of green spaces. A greenness score is derived from this data which is used to conduct a statistical analysis on your responses.
- **Security and Anonymity:** The security of your data and your anonymity are prioritised throughout the study. All data is securely stored, accessible only to myself. All data will be permanently deleted upon cessation of this study.

Understanding PANAS Scores

- **Purpose:** The Positive and Negative Affect Schedule (PANAS) score is a key tool in this study which helps in understanding your emotional well-being in relation to your environment.
- **Structure:** You will be asked two questions which reflect your positive affect score, and two which reflect your negative affect score.
- **Usage:** Your responses to the surveys are used to calculate your PANAS score, reflecting your emotional state during the walk.

Results and Feedback

At the end of your walk, you will receive a composite image comprising all the photographs you've sent, along with a graph illustrating the changes in your emotional well-being throughout your walk.

Voluntary Participation and Study Duration

- **Voluntary Participation:** Your participation in this study is completely voluntary. You are free to withdraw at any time without any consequences.
- **Study Duration:** Please note that this system will be operational until December 7th 2023.

Need Help?

If you require assistance or more information at any point, type 'help' in the chat to receive a link to a help document.

If you have engaged with the help document and the system stops working, please email me at uu19561@bristol.ac.uk.

Thank you for considering participation in this study.

For any further inquiries, feel free to reach out via the email provided above.

Figure 2: Participant Information Sheet

```java
// Main processor of conversation logic, inherited by SurveyConversationHandler and
NewUserConversationHandler
public abstract class ConversationHandler {

    private final Conversation conversation;

    public ConversationHandler() {
        this.conversation = new Conversation(getSurveyMessages());
    }

    public Conversation getConversation() {
        return conversation;
    }

    protected abstract void validateResponse(int position, Response response) throws
ResponseInvalidException;

    public abstract boolean handleResponse(MessageSender sender, Response response) throws
ConversationHandlerException;

    // Start the next survey
    public void startSurvey(MessageSender sender) throws ConversationHandlerException {
        try {
            sender.sendMessages(getInitialMessages());
        } catch (InterruptedException e) {
            throw new ConversationHandlerException(e);
        }
    }

    // Determines whether to end a survey
    public boolean handleNextSurveyStep(MessageSender sender) throws
ConversationHandlerException {
        conversation.advancePosition();

        // If there is another message left in the message list, send next messages
        if (conversation.hasNextMessageList()) {
            try {
                sender.sendMessages(conversation.getCurrentMessageList());
            } catch (InterruptedException e) {
                throw new RuntimeException(e);
            }
            return false;
        } else {
            return handleEndOfSurvey(sender);
        }
    }

    public abstract boolean handleEndOfSurvey(MessageSender sender) throws
ConversationHandlerException;
    public abstract List<String> getInitialMessages();
    public abstract List<List<String>> getSurveyMessages();
}
```

Figure 3: Abstract Conversation Handler Class

```java
// Implemented to handle RPS rate limit exceeded if multiple participants interact with
system simultaneously
  public void exponentialBackoffRetry(int maxRetries, long initialDelay, Runnable task)
throws InterruptedException {
    long delay = initialDelay;
    int retries = 0;
    while (retries < maxRetries) {
      try {
        task.run();
        // Exit retry loop upon success
        break;
      } catch (TwilioException e) {
        Thread.sleep(delay);
        // Exponential backoff doubles the delay after each attempt
        delay *= 2;
        retries++;
      }
    }
  }


  public void sendImage(String imageUrl) throws InterruptedException {
    PhoneNumber recipientPhoneNumber = new PhoneNumber(participant.getTelephoneNumber());

    exponentialBackoffRetry(3, 1000, () -> {
      Message message = Message.creator(
                      recipientPhoneNumber,
                      sendPhoneNumber,
                      "")
              .setMediaUrl(
                      List.of(URI.create(imageUrl)))
              .create();
      // Print record of message sent to terminal to enable easy checking if system is
functioning
      System.out.println(participant.getTelephoneNumber() + " " + message.getSid());
      try {
        Thread.sleep(500);
      } catch (InterruptedException e) {
        throw new RuntimeException(e);
      }
    });
  }

  public void sendMessages(List<String> messages) throws InterruptedException {
    PhoneNumber recipientPhoneNumber = new PhoneNumber(participant.getTelephoneNumber());

    exponentialBackoffRetry(3, 1000, () -> {
      for (String textBody : messages) {
        Message message = Message.creator(
                        recipientPhoneNumber,
                        sendPhoneNumber,
                        textBody)
                .create();
        System.out.println(participant.getTelephoneNumber() + " " + message.getSid());
        try {
          Thread.sleep(500);
        } catch (InterruptedException e) {
          throw new RuntimeException(e);
        }
      }
    });
  }
```

Figure 4: Message Sending Class Using Twilio API

```java
  // Defines greenspace labels
  private static final Set<String> greenSpaceLabels = Set.of(
          "dandelion", "garden", "grass", "grassland", "landscape", "lawn",
          "meadow", "park", "pasture", "tree", "woodland", "nature reserve",
          "vine", "flower", "bush", "forest", "plant", "greenhouse",
          "orchard", "flowerpot", "vegetation", "garden roses", "wildflower",
          "plantation", "shrub", "flowering plant", "agricultural land",
          "agricultural area", "rural area", "botanical garden");

  // Generates the image greenness score by comparing greenspace labels to total labels
  public static float analyseImage(String imagePath) throws IOException {
    float aggregateAnnotationScores = 0;
    int greenSpaceAnnotations = 0;
    int nonGreenSpaceAnnotations = 0;

    ByteString imgBytes = getImgBytes(imagePath);

    // Builds the image annotation request
    List<AnnotateImageRequest> requests = new ArrayList<>();
    Image img = Image.newBuilder().setContent(imgBytes).build();
    Feature feat = Feature.newBuilder().setType(Feature.Type.LABEL_DETECTION).build();
    AnnotateImageRequest request =
            AnnotateImageRequest.newBuilder().addFeatures(feat).setImage(img).build();
    requests.add(request);

    // Perform the request
    try (ImageAnnotatorClient client = ImageAnnotatorClient.create()) {
      List<AnnotateImageResponse> responses =
client.batchAnnotateImages(requests).getResponsesList();
      for (AnnotateImageResponse res : responses) {
        if (res.hasError()) {
          System.out.printf("Error: %s\n", res.getError().getMessage());
          return 0;
        }

        // Check for labels and classify them
        for (EntityAnnotation annotation : res.getLabelAnnotationsList()) {
          String label = annotation.getDescription().toLowerCase();
          if (greenSpaceLabels.contains(label)) {
            aggregateAnnotationScores += annotation.getScore();
            greenSpaceAnnotations++;
          } else {
            nonGreenSpaceAnnotations++;
          }
        }
      }
    }

    // Calculate final score considering both types of annotations
    if (greenSpaceAnnotations == 0) {
      return 0;
    } else {
      float greenSpaceScore = aggregateAnnotationScores / greenSpaceAnnotations;
      float deduction = (float) nonGreenSpaceAnnotations / (greenSpaceAnnotations +
nonGreenSpaceAnnotations);
      return Math.max(greenSpaceScore - deduction, 0);
    }
  }
```

Figure 5: Image Analysis Method Using Google Vision API

```java
public class S3ImageUploader {
  private static final String BUCKET_NAME = "";
  private static final String ACCESS_KEY_ID = "";
  private static final String SECRET_ACCESS_KEY = "";
  private static final Region REGION = Region.EU_WEST_2;

  public static String imageUploader(String key, String filePath) {
    // Set up AWS credentials and S3 client
    AwsBasicCredentials awsCreds = AwsBasicCredentials.create(ACCESS_KEY_ID,
SECRET_ACCESS_KEY);
    S3Client s3 = S3Client.builder()
            .credentialsProvider(StaticCredentialsProvider.create(awsCreds))
            .region(REGION)
            .build();

    // Upload image
    PutObjectResponse response = s3.putObject(PutObjectRequest.builder()
                    .bucket(BUCKET_NAME)
                    .key(key)
                    .build(),
            Paths.get(filePath));

    if (response.sdkHttpResponse().isSuccessful()) {

      // Construct the URL of the uploaded image
      return String.format("https://%s.s3.%s.amazonaws.com/%s", BUCKET_NAME,
REGION.toString(), key);
    } else {
      // Return nothing if unsuccessful
      return "";
    }
  }
}
```

Figure 6: AWS S3 Bucket Image Uploader

```python
import geopandas as gpd
from shapely.geometry import Point
import pandas as pd
import os

# Load greenspace data
green_spaces = gpd.read_file('opgrsp_essh_gb/OS Open Greenspace (ESRI Shape File)
GB/data/GB_GreenspaceSite.shp')


def calculate_score(participant_point, green_spaces):
    # Create 300 metre buffer around point
    buffer = participant_point.buffer(300)

    # Find greenspace intersection with buffer
    intersecting_green_spaces = green_spaces[green_spaces.intersects(buffer)]

    # No greenspaces within 300m
    if intersecting_green_spaces.empty:
        return 0

        # Calculate total area of greenspaces in buffer
    total_green_area = intersecting_green_spaces.intersection(buffer).area.sum()

    # Calculate buffer area
    buffer_area = buffer.area

    # Calculate the proportion of  buffer covered by greenspace
    return total_green_area / buffer_area


# Read workplace location data
participants_df = gpd.read_file('coordinates.csv')
# Create geometry object column
participants_df['geometry'] = participants_df.apply(lambda row: Point(row.Longitude, row.Latitude),
axis=1)
# Create geopandas data frame
participants_gdf = gpd.GeoDataFrame(participants_df, geometry='geometry')

# Convert coordinate system so compatible with greenspace data (WGS 84)
participants_gdf.set_crs("EPSG:4326", inplace=True)
participants_gdf = participants_gdf.to_crs(green_spaces.crs)

# Process individual file
participants_gdf['score'] = participants_gdf['geometry'].apply(lambda x: calculate_score(x,
green_spaces))
# Create file containing workplace location data
participants_gdf.to_csv('workplace_greenness.csv', index=False)

# Process participant walk data
folder_path = 'participantdata'
combined_df = pd.DataFrame()

for filename in os.listdir(folder_path):
    if filename.startswith("participant") and filename.endswith(".csv"):
        file_path = os.path.join(folder_path, filename)

        participants_df = gpd.read_file(file_path)

        participants_df['geometry'] = participants_df.apply(lambda row: Point(row.Longitude,
row.Latitude), axis=1)
        participants_gdf = gpd.GeoDataFrame(participants_df, geometry='geometry')

        participants_gdf.set_crs("EPSG:4326", inplace=True)

        participants_gdf = participants_gdf.to_crs(green_spaces.crs)

        participants_gdf['location greenscore'] = participants_gdf['geometry'].apply(
            lambda x: calculate_score(x, green_spaces))

        # Save file containing greenness scores
        output_filename = f'location_greenness_{filename}'
        output_file_path = os.path.join(folder_path, output_filename)
        participants_gdf.to_csv(output_file_path, index=False)
```

Figure 7: Python Code for Analysing Location Greenness

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