STUDENT MENTAL HEALTH PROFILING FOR TARGETED AND PERSONALISED SUPPORT INTERVENTIONS

Carly Palmer Foster, BA (Hons), MSc

January 2023

This thesis is submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy

Department of Educational Research
Lancaster University
UK

Abstract

This research used mixed methods to explore how universities may incorporate profiling into their mental health support packages by creating student mental health profiles to target and personalise pastoral care. There were two research questions which ask what types of data can be used to create such profiles and how they may be used in practice by staff.

Quantitative methods were used to collect mental health data via the WHO-5 survey; the data was analysed and combined with other student data based on known risk factors to create a series of student mental health profiles. The profiles were presented to a university mental health team via a presentation and then qualitative data was collected via semi-structured interviews to explore staff perceptions of profiling.

In total, 28 profiles were created, and eleven use cases were identified for their application in university settings. This study found the rate of students' completion of the WHO-5 survey varied during the year with method of data capture significantly impacting participation rates. The data and resulting clusters supported the creation of profiles with 2 or 3 optimal clusters for each dataset.

Whilst some profiles were limited in context beyond the WHO-5 data they did facilitate use cases which staff identified as being applicable to targeting and personalising support. Including additional contextual data about students did not increase the quantity of viable clusters but did improve the quality of the resulting profiles in terms distinctiveness and staff understanding.

This research finds SMHP is an approach capable of facilitating targeted and personalised support for *all* students in university settings- not just those at risk and seeking help. Profiling has been found to have many other use cases not previously explored in the literature. The approach requires further investigation into more relevant variables at the positive end of the wellbeing spectrum and service designers should be aware of the areas where further research is recommended.

WORD COUNT: 47,860

Included in this are the main text of the thesis, footnotes, data and text incorporated into diagrams, tables or figures[1]

[1] As per the Thesis Template TRRandDPER February 2022

Contents

List of Tables

List of Appendix Tables

List of Figures

List of Appendix Figures

List of Abbreviations

CMH	Counselling and Mental Health (team)
CRM	Customer Relationship Management System
EQLS	European Quality of Life survey
HE	Higher Education
HPU	Health Promoting University
MHW	Mental Health and Wellbeing
OFS	The Office for Students (the independent regulatory body responsible for UK Higher Education)
PWP	Psychological Wellbeing Practitioner
SMHP	Student Mental Health Profiling
SRS	Student Records System
UUK	Universities UK (an organisation representing universities in England, Scotland, Wales and Northern Ireland.)
UK	United Kingdom
VLE	Virtual Learning Environment
WHO-5	The World Health Organisation - Five Wellbeing Index

Acknowledgement

The desire to be my best self was never as strong as the day my daughter was born. You're my inspiration, Faby. Yet, as a single parent who started a PhD with a seven-week-old babe in arms, I have spent the last six and a half years on a high stakes journey of self-discovery. It's been rough but I have come to understand the meaning of community, friendship and love that I can only begin to acknowledge here.

Firstly, I would like to thank my parents Michelle, Robert, my grandma Marlene and also Denise and Kerr who have had to endure this PhD with me and supported me to 'crack on' for longer than we all expected. From childhood, you have pushed me and I'm grateful even if I don't always seem it.

Secondly, my friends, Rachel, Claire, Simon and Jemma whose support has extended far beyond the occasional Saturday afternoon childcare (allowing me precious time in the basement of the library), and whose belief in me that I could do this never wavered. Thanks guys, Faby and I are so grateful we have you.

Thank you to colleagues who have inspired me to push forward to academic success, particularly Professor Peter Francis for encouraging me to write down my ideas and to value real quality. You fanned the flame at the beginning and I have evolved more than you know because of your guidance.

I am grateful to the OFS student mental health analytics project and its collaborators for allowing me to contribute to such an important topic for the sector.

I am immensely grateful to Lancaster University who have supported me to undertake the doctoral programme via a financial scholarship; without this support the journey would not have been possible. Know that it has enriched my life and in turn that of my daughter and I am truly grateful. Such support is life changing and reinforces my love of Higher Education and its place in society. My gratitude also to my supervisor Gemma Derrick for her feedback and faith.

A final and most heartfelt thank you to Dr Guy Brown for his endless interest, compassion, advice and support of this work and for championing me to be the academic I've always dreamed of being.

Because of you all, I made it.

For Philip Brooke, whose dedication to supporting students with their mental health never faltered.

Declaration

The author declares no conflict of interest. All work presented in this thesis is the author’s own. The author acknowledges financial support from Lancaster University.

Signature ______________________________________

1. Introduction

1.1. Background

Discourse on student mental health and wellbeing (MHW) is becoming a more prominent feature of Higher Education (HE) as levels of disclosure are exponentially on the rise amongst applicants (Tressler, 2017) and the student population (Thorley, 2017). Recently, policy frameworks promote a sector-wide agenda to prioritise student mental health (Universities UK, 2018 and 2020; Office for Students, 2019) and the UK government recognises that visible investment in this area is essential to meet growing demand for services (Hazell, 2020). The volume of applicants to UK universities continues to increase (UCAS 2022 statistical release[2]), yet few assume the increase in mental health and wellbeing issues correlates to increased student numbers and cite more complex factors[3]. It is even argued that the UK's widening participation agenda has had a role to play in worsening levels of student mental health (Macaskill, 2013) although such conjecture promotes a sense of deficit discourse on why students' health is worsening rather than why university services are failing to meet the need.

Whilst there has undoubtedly been a culture shift over the last few decades in HE, the impact of initiatives such as widening participation is not explicitly documented or evidenced in the literature; however circumstantial proxies such as financial insecurity and family support, are amongst known risk factors (Cooke et al, 2004; Storrie, Ahern and Tuckett, 2010; Macaskill, 2013; Pedrelli et al., 2015; Brown, 2016; Royal College of Psychiatrists, 2021). Despite a wealth of analysis on risk factors for student mental health, a 2013 study cited that 94% of students believe that 'Anyone can suffer from mental health problems' (Cardwell et al., 2013). A decade on, declaration rates are growing and there is still more to do to address the issue that students are less likely to talk about MHW than other members of the population (Cardwell et al., 2013). In addition to the growing body of research on quantifying the student mental health

[2] Available at https://www.ucas.com/data-and-analysis/undergraduate-statistics-and-reports/ucas-undergraduate-releases/applicant-releases-2022-cycle/2022-cycle-applicant-figures-26-january-deadline, accessed on 16th June 2022
[3] See Student Minds, 2017, for students' lived experiences of the pressures of university life

‘problem’, there is corresponding enquiry into potential solution[4]. Recommendations for impactful response strategies offer an evidence-based starting point to reduce the number of students developing serious MHW problems (Royal College of Psychiatrists, 2021) with the promotion of mental health support for *prevention* as important as intervention (WHO,2021). Commonly cited solutions to the problem are better linkage between universities and external health agencies (World Health Organization, 2008) as well as addressing the underlying issues of stigma and barriers to help-seeking (Eisenberg et al., 2009), lack of awareness both of the problems and possible solutions available (Quinn et al, 2009; Li, Dorstyn and Denson, 2014).

The direction of travel for recent policymakers in the UK has been improved utilisation of data and technology ‘to establish baselines and measure outcomes’ (UUK - Universities UK, 2020, 27). Universities are encouraged to develop and deploy interventions, either proactive or reactive operating at either individual or population level and may focus on acute cases of poor mental health or more generalised wellbeing. Universities are simply not in a position to resource endless ineffective or irrelevant programmes therefore what is crucial to mentally healthier student bodies is to ensure that interventions are targeted at the right students, at the right time and scaled to students’ individual needs based on a hierarchy of service offerings.

1.2. The Role of Data and Technology

In marketing, targeted and personalised advertising means using data to deliver highly relevant and timely campaigns. In the context of this research, targeted and personalised support borrows from this approach and means MHW interventions scaled to students’ personal circumstances and severity of need, offered at the point in time considered to be most impactful to them.

Student mental health profiling (SMHP) is a data-driven approach which aims to support the effective targeting of wellbeing interventions when operating at scale i.e. to improve wellbeing for all students at a university. Such an approach may seem daunting in terms of the volume of resource required to support all students however

[4] See Conley, Durlak and Kirsch, 2015, for a meta-analysis of mental health prevention programs in HE

it assumes a quantifiable relationship between data inputs e.g., gender and age and data outputs e.g. mental health scores which can in turn influence a hierarchy of need. Such a hierarchy can be used to positively utilise resources rather than exacerbate constraints.

By collecting, processing and analysing data points for individual and groups of students, an algorithm may search for patterns between students' demographic, behavioural and/or circumstantial inputs and their mental health outcomes. The theory of change for SMHP is like other similar educational analytics approaches (see Francis and Foster, 2020) whereby analytical tools are deployed on student datasets to yield a more comprehensive and real-time view of a student to support taking action on specific 'profiles'.

Profiles allow the grouping of students who display similar data traits, rather than dealing with one large homogenous population. SMHP hypothesises a positive impact on wellbeing; interventions which are data-informed should lead to more meaningful and timely support which is more relevant to individual students or student groups than a generic, population-wide service would have been.

1.3. Aims and Objectives of the Research

I came to this research topic through my background as a higher educational professional with pastoral care responsibilities for the entire student body at a strategic level. Having utilised and evaluated data analytics to support student continuation (Foster, 2020; Foster and Francis, 2019), it became apparent that, when intervening with students proactively on continuation risk factors (such as academic performance or engagement), the intervention uncovered an underlying mental health issue which the student had not disclosed or even recognised as relevant. I became conscious that even with increased rates of disclosure, there remained a silent population of students who may benefit from support if it were proactively offered and scaled to their need.

As such, I wanted to further an understanding of how university services could be positioned to identify who needs support in the population, with what level of urgency and with what level of personalisation to their specific wellbeing circumstances. As such my attention turned to assessing the viability and validity of such approaches for university mental health teams with increased caseloads yet there appeared to be a gap in sector knowledge and practice on how to implement proactive digital approaches to servicing student wellbeing at population level and for all levels of severity- including those with positive wellbeing. Furthermore, whilst HESA regulations ensure that each institution collects a base level of data which is available to inform service design, data is not always available or useful at the individual student level nor is there sector guidance on how it may be leveraged for promotion, prevention and intervention.

As such, this thesis aims to explore how university student services teams use student-level data for the improved design and delivery of targeted and personalised mental health and wellbeing support packages for the whole student body. It will achieve via an exploratory study to answer the following research questions;

RQ1: How can student mental health profiles be created using WHO-5 data and data on known risk factors?

RQ2: How might university student services staff implement mental health profiling as a Whole University approach to targeted and personalised mental health and wellbeing support?

By collecting, clustering and analysing data, the thesis explores mental health data availability and validity for informing support across a student population. Descriptive data is used in an interpretive process to create profiles from the clusters; profiles may be static at key points in the student journey (such as enrolment, end of semester and pre-assessment), or longitudinal reflecting on a change between those key points. Informed by the existing literature on the risk factors pertaining to poor student mental health and wellbeing, the thesis goes on to explore how profiles may be further defined via the consideration of a wider variety of data. RQ1 promises to give a comprehensive view of the viability of SMHP within a university setting but also explores the reality of such activities including data capture mechanisms and students' perceptions of data privacy.

Qualitative reflections from staff are used to provide commentary on the perceived validity of the profiles identified in the first section of analysis however, where RQ1 looks to appraise how data may be used to create student mental health profiles, RQ2 seeks to understand how and with what purpose such profiles may be deployed in a real university setting. This includes an appraisal, by those employed in a university Counselling and Mental Health (CMH) team, of their propensity to use data and profiling in this way. The analysis of the data collected explores their perception of their own individual roles as well as the role of a university mental health and wellbeing service. Use cases are identified which can be considered by service designers to evaluate roles and responsibilities, organisational structuring and resource investment and institutional capacity for targeting and personalising interventions for a whole university population.

1.4. Structure of the Thesis

Chapter 2 presents the *Literature Review* in four parts; (i) the role of universities in the promotion of mental health for all students, not just those in need, which leads on to an overview of studies around (ii) measuring and managing students' mental health. This part of the literature concludes with some of the challenges of a one size fits all approach within a diverse university population which leads on to an exploration of (iii) targeted and personalised support strategies and the role of data and technology to enable such approaches. The literature review concludes with a discussion on (iv) profiling for intervention and service design, considering some notable examples in the existing literature and highlighting the opportunities and potential pitfalls for its deployment within a university CMH team. A summary of the literature review is provided so as to present those aspects which directly feed into the next chapter and the decisions made relating to how this research was conducted.

Chapter 3, *Methodology*, begins with a brief discussion on the relationship that this project has to a funded project by the Office for Students for clarity and transparency. The theoretical underpinnings of the study – relativism and pragmatism – are discussed reflectively. The chapter then outlines the decision to adopt a mixed methods approach to the design of student mental health profiles and their potential use cases, as identified by staff, with respect to targeted and personalised mental health and wellbeing support packages.

Chapter 4, *Results*, begins with an overview of the WHO-5 data collected, offering a descriptive analysis of the trends at the three survey census points. The chapter then documents the outputs of the data clustering process followed by a section on the translation of these clusters into 'student mental health profiles'. The results chapter then progresses to the qualitative findings of the interviews with university staff and is structured based on their reflections to targeted and personalised support, profiling as a mechanism to achieve this and critical feedback on the actual profiles created in the research. This section culminates in a series of use cases identified through the analysis of data.

Chapter 5, *Discussion*, represents the interpretation of the results from Chapter 4 in two sections. The first section evaluates whether mental health profiles can be created from mental health data, and data on known risk factors. Where part one asks whether they can be created, section 2 asks whether they should be, what they may be practically used for and by whom. This final section considers the roles and responsibilities within a CMH team and the extent to which the profiles may be adopted for effective use in addressing the challenges the sector faces with respect to meeting the pastoral needs of students.

Finally, the thesis ends with Chapter 6, *Conclusions*, which outlines the contribution to knowledge, theory and practice that this thesis has made. An honest appraisal of the limitations of the research is offered alongside recommendations for how it may be further developed and implemented.

2. Literature Review

2.1. Health Promoting Universities

Universities operate as 'settings for health' a term which the WHO defines as "The place or social context in which people engage in daily activities in which environmental, organizational, and personal factors interact to affect their health and wellbeing". (WHO, 1998). Although this definition is impractically broad for immediate application within HE research, the healthy settings approach inspired intra-sector networks including Health Promoting Universities (HPU); this particular initiative hones the scope of the WHO definition and provides a foundation for academic enquiry on HE mental health strategies. Tsouros et al. (1998) collated a series of case studies covering aspects of health promotion within HE which called for "whole-campus policies on individual risks" (Beattie, 1998) and embedding health promotion "across the university as a whole" (Dowding and Thompson, 1998). This agenda has evolved over the last two decades and in a UK context the term 'a whole university approach' (Thomas, 2002; UUK, 2020) is now used for holistic approaches which promote student mental health and wellbeing.

Whole University approaches offer enormous potential for health and wellbeing promotion across both the staff and student population (UUK, 2020) and institutions have a responsibility to be active, problem-solving agents (Cawood, Dooris and Powell, 2010). Tsouros et al. (1998) suggested that there are three ways that universities can add value to the health promotion agenda;

> "1) by protecting the health and promoting the well-being of students, staff and the wider community through their policies and practices, 2) by increasingly relating health promotion to teaching and research, and 3) by developing health promotion alliances and outreach into the community" (Tsouros *et al*., 1998, 122-123).

However, despite a growing understanding of the HPU concept it has been suggested that translating the vision into consistent action remains an ongoing challenge, particularly for complex institutions where whole system approaches are still to be implemented (Suarez-Reyes, Serrano and Van den Broucke, 2018). Evidence to suggest the approach is effective in practice is inconclusive (Newton, Dooris and Willis, 2016) and even with institutional commitment, key challenges remain. University populations are large, diverse and heterogenous therefore a whole university approach which is 'one size fits all' is problematic due to scale, complexity and a lack of specificity (Newton, Dooris and Willis, 2016; Priestley et al., 2021).

Despite this and given the increase in student mental health disclosure, whole university approaches have become the cornerstone of UK HE policy on pastoral care (Hughes and Spanner, 2019; UUK 2020). Sector bodies are imploring HEIs to explore new ways of serving the wellbeing needs of the student population (UUK, 2015; Royal College of Psychiatrists, 2021). One notable contribution is The University Mental Health Charter[5] (Hughes and Spanner, 2019), a UK- based framework funded by the University Partnerships Programme (UPP) foundation and the OfS.

When developing settings-based approaches Ashton (1998) suggests learning from others within the wider network and proposed the healthy prisons model as a starting point for the HPU model. The first step within this model is to measure demography and establish a baseline of the population's characteristics, needs and risk factors (Ashton, 1998). The next section explores the demography of student mental health and wellbeing to understand its measurement, the known risk factors and challenges to meeting students' needs.

2.2. Measuring and Managing Student Mental Health Support

2.2.1. Measuring student mental health

Measuring mental health is core to measuring quality of life (OECD, 2014) and students themselves argue that it should be considered ubiquitous and pervasive; 'you don't have to be diagnosed with anything specifically, but anyone can feel quite low or anxious one day just like one day feeling 'under the weather' with a cold or flu.' (Student Minds, 2017, 12). Yet population level mental health surveillance is particularly

[5] The work was created collaboratively across the sector with by students, staff, institutional leaders and Student Minds, a charity representing student mental health in the UK. The full charter is available at https://universitymentalhealthcharter.org.uk accessed on 15/07/2022

challenging (Ayers et al., 2013) so new technologies which track sleep patterns and collect near real-time self-reported wellbeing seek to address this and have been used to forecast outcomes (Spathis et al., 2019). In a UK HE context, the collection of some mental health data is now mandatory to allow reporting on sector trends[6] and monitoring of support such as take-up of the Disabled Students' Allowance. The regulatory body HESA (Higher Education Statistics Agency) stipulate that institutions should return student data on "A mental health condition, such as depression, schizophrenia or anxiety disorder"; this relies on the illness not only being diagnosed but also disclosed to the institution which is a known barrier (see 2.2.4). Here a mental health condition is defined as an impairment impacting a student's basic activities, however, attempts to quantify student mental health often occur on a much broader scope to analyse the trends (Macaskill, 2013) and identify risk factors (Sharp and Theiler, 2018).

In any research the timing of data capture is important (Creswell, 2009), but this is particularly the case for mental health data due to the prevalence of seasonal affective disorder (Ayers et al., 2013). However, there are examples in the literature where researchers report a conscious avoidance of timepoints when mental health is expected to be lower (e.g. assessment time) 'to limit the effect' of seasonal influences (see Sam and Eide, 1991, 24); such research design is counterintuitive to ascertaining a realistic understanding of student wellbeing across the year. Furthermore, the literature highlights that, to get to such a sophisticated model of student wellbeing, mental health must be measured continually (El Ansari et al., 2011; Ayers et al. 2013) with some studies opting for multiple census points to capture a longitudinal picture (Andrews and Wilding, 2004; Conley et al., 2020). Conley et al. (2020) reported a study of 5,532 students; they created a baseline two weeks before students started university and covered a four-year period. Bewick et al (2008) created their mental health baseline at a similar time during 'autumn semester'.

Wider than an HE context, Spathis et al. (2019) found that using one day's worth

[6] See HESA website https://www.hesa.ac.uk/collection/c19051/a/disable accessed on 02/02/2022

of self-reported wellbeing data in the general population can adequately predict wellbeing 3 weeks from capture but that there was variability in wellbeing by days of the week which impacted the efficacy of the predictive tool; this data was collected sparsely on a continuous basis in the wild and so is posited to be more realistic than purposefully contained study samples like the majority of other literature reviewed. There were no examples found of this latent, longitudinal, at-scale methodology being deployed in an HE setting.

When reviewing academic methodologies to understand timing of data capture, it was also possible to examine the sample sizes within the primary research. Many of the studies looking to quantify mental health issues do so with relatively low sample sizes; a systematic review conducted by Harrer et al. (2018) found that the range of sample sizes for mental health intervention studies was between 38 to 2,638 (Harrer et al., 2018). Although these were for internet interventions specifically, this figure is in line with the literature reviewed for this study which spanned between 175 (Julal, 2015) to 5,532 (Conley et al., 2020) for single institution projects. One study found that 322 medical students (57.1% of the total population) answered a mental health questionnaire and that younger students were over-represented (Tija, Givens and Shea, 2005) which is a similar response rate to Andrews and Wilding (2004) which obtained 76% response rate in the first mental health survey (n = 676 / 890) and 60% response rate in the second (n = 351/ 585). From a qualitative perspective, Martin (2010) posted a survey online to 1,517 students and only 54 responded thus representing 3.6% of the eligible population although this was deemed sufficient for a qualitative research design. Some studies such as Drum et al. (2009) and The Healthy Minds Study (Eisenberg, Lipson and Heinze, 2010) pooled data from across multiple universities and achieved larger sample sizes (26,451 and 32,754 respectively) however these were rare and the proportion of the eligible populations was still small (24.4% and 14% respectively).

2.2.2. Tools to Quantify Student Mental Health and Wellbeing

A 2016 YouGov survey found that depression and anxiety are the most commonly reported mental ailments in a population sample of 1,061 students (Smith,2016). It is therefore unsurprising that attempts to quantify student mental health often rely on clinal tools with a focus on these ailments; approaches which have been developed in healthcare practice and have been deployed in university settings with students include;

- the CORE-OM and CORE-10 for psychological distress (see Bewick et al., 2008 and Broglia, 2021)
- the PHQ-9 for anxiety and depression (see Eisenberg, Golberstein and Gollust, 2007)
- the Beck Depression Inventory (BDI) (see Tija, Givens and Shea, 2005)
- the Zung Depression scale (see Golinger, 1991)
- the GAD-7 for generalised anxiety (see Grineski et al., 2021)
- the General Health Questionnaire (GHQ-28) (see Macaskill, 2013)
- the Hospital Anxiety Depression Scale (HADS, see Andrews and Wilding, 2004).

Non-clinical tools used in the analyses of student mental health include the Depression, Anxiety and Stress Scales (DASS-21) (Larcombe, Baik and Finch, 2022) and the Short Warwick Edinburgh Mental Wellbeing Scale (Byrom et al., 2020). The Symptoms and Assets Screening Scale (Downs et al., 2013) is a 34-item tools designed specifically to assess student mental health problems at a population level; although validated with adequate reliability in most areas, the tool has had very little research application since its development. Downs et al. also utilised the WHO-5 score (Downs et al., 2017) for screening of general wellbeing in the population which has only 5 items and is therefore considerable shorter. Both the projects reviewed by Downs et al (2013, 2015) showed a desire to develop adequate screening tools for the student population but neither have been validated for subsequent intervention.

Other studies utilising the WHO-5 include a study in Hong Kong alongside the CD-RISC-10 tool which measures resilience (Chow et al., 2018); this study reported a population sample mean WHO-5 score of 15.5 (unscaled). It does not stipulate at which point in the academic year it was captured. Another example of the use of the WHO-5 is a 2015 study into balancing the demands of working while studying; this reported an unscaled mean WHO-5 score of 16.19 for the 185 respondents although again the timing of the survey is not explicit (Creed, French and Hood, 2015). Although not in an HE context, the European Quality of Life Survey (EQLS) utilised the WHO-5 measure for population level screening, providing mean results by sex, age and income for the 28 member states (see "EQLS – Data Visualisation", 2016); it reports an average WHO-5 score of 63 for the general UK population.

The majority of studies looked to correlate variables with negative health outcomes such as stress and anxiety (Cossy, 2014); some notable studies where positive indicators were used include Larcombe, Baik and Finch's use of the Psychological Well-Being (PWB) scale and The Thriving Quotient (Schreiner, 2010) was developed to understand student success (though notably not mental health or wellbeing) from a positive, affirming perspective of student behaviours and community.

2.2.3. Risk factors

It should be noted that there is extensive research on the predictors of mental health in the general population, all of which relate to students but are not specific to the student experience, including events which lead to Post Traumatic Stress Disorder (PTSD) (O'Brien, 1998). This review has excluded these trauma-related risk factors to focus on factors relating to the student experience given that the current research context to utilise and leverage datasets available to university mental health teams.

Studying for a degree can have a direct influence on students' personal health (e.g., exam-related stress and fear of academic failure) and can further conflate existing wellbeing factors at play in students' lives (Student Minds, 2017). Furthermore, mental illness and illbeing does not discriminate, it can impact any student during their academic journey which has led to attempts to understand the signals of risk that indicate a student may need support (ibid). To inform the research design for the present study, a brief review of known risk factors, within the context of student mental health specifically, has been conducted and categorised into four areas; (i) demographic factors; (ii) academic factors; (iii) Family, community and lifestyle factors; and (iv) Personality and metacognitive factors.

2.2.3.1. Demographic factors

Studies in student mental health have investigated demographic correlates with MHW outcomes and found significant differences by gender, age and nationality (Cooke et al., 2004; EQLS, 2016; Thorley, 2017; Conley et al., 2020).

The 2016 EQLS found that the average WHO-5 score in the UK was 5 points lower for females compared to males (66 versus 61, see "EQLS – Data Visualisation", 2016). Surveys specifically within the student population have found a similar pattern for female students (Smith, 2016) although the extent to which this is driven by more open disclosure amongst the female population is unclear; 'female students are now significantly more likely than male students to disclose a mental health condition to their HEI' (Thorley, 2017, 22). Some studies have found that men score worse on mental health surveys than women e.g. a 2004 study found that male students reported poorer scores on two aspects of the GP-CORE questionnaire; 'I have felt warmth and affection for someone' and 'I have felt I have someone to turn to for support when needed'; international students also scored lower on these questions (Cooke et al., 2004).

Studies have also found age-related factors which impact student wellbeing whereby younger students often report lower levels of mental health problems (Thorley, 2017). This is not consistent with the EQLS survey (see Table 1 overleaf) which reports those aged 50-64 to have the lowest rate of wellbeing in the population; this suggests that, for younger students, wellbeing issues may be exacerbated if the individual is in a university setting. A positive finding in the literature is that younger students have been found to be more prevalent adopters of avoidance focussed coping (AFC) which is a metacognitive strategy to avoid mental distress (Solhaug et al. 2019).

Table 1 UK Average WHO-5 by age category as per the 2016 EQLS Data Visualisation Tool

Age Category	*Average WHO-5 for UK population*
18-24 year olds	66
25-34 year olds	62
35-49 year olds	64
50 – 64 year olds	61
65+	65
Whole Population	**63**

As studies and policy evolve to identify behavioural variables which University Support Services may influence, quantitative research may opt to control for demographic variables within quantitative models (e.g., Hysenbegasi, Hass and Rowland, 2005).

2.2.3.2. Academic engagement and outcomes factors

The 2016 YouGov survey reported that 71% of students cited university work as their main source of stress (Smith, 2016) with academic success operating as both positive stimuli and negative 'stressors' (Monk, 2004). Although some challenge the idea that academic stress is the sole driver for poor student mental health (Golinger, 1991), there are studies which cite it as a key intercorrelate with other factors such as psychological capital (Martínez et al., 2019) and help-seeking behaviours (Aldalaykeh, Al-Hammouri and Rababah, 2019).

Larcombe, Baik and Finch (2022) conducted a study which aimed to deconstruct and further understand the academic stressors which impact student MHW by starting with a demographic model and then adding contextual data. Their study found that course experiences (variables such as assessment stress and teacher recognition) contributed more to the accuracy of a predictive model for mental health than demographic variables (e.g., gender and age) and situational variables (e.g. students' perceptions of their finances, future employment prospects and English language skills). There were no examples of literature which analysed correlations between student wellbeing and grades or module outcomes.

2.2.3.3. Family, community and lifestyle factors

When considering risk factors associated with student mental health, it’s imperative to consider students’ personal circumstances and how their lifestyles interact with their mental health as studies have found that stress occurs in students due to poor sleep patterns (Byrom, 2020), and nutrition and physical activity (Di Bendetto, Towt and Jackson, 2020). To address this, studies have attempted to account for lifestyle factors in the clustering process (ibid). Employment pressures should also be considered because it has been evidenced that having a job while studying can have both a positive and negative impact on a students’ wellbeing and university experience (Creed, French and Hood, 2015). Monk (2004) cites finance to be a particular stressor for students however the results are not compelling stemming from small sample sizes impacting t-test validity. The wellbeing impact on students’ perceptions of debt were investigated by Cooke et al. (2004) who found significant correlation in all three years of study between financial concerns and mental health ($p < 0.001$ in all cases). Causality is however unclear in this study in that it suggests students’ mental health deteriorates as debt worries worsen but doesn’t acknowledge that debt worries may reduce as mental health improves due to improved psychological reasoning e.g., resilience, coping and self-esteem. Furthermore, whilst *current* lifestyle impacts mental health, the pressures of ‘making the right choices’ and studying to realise a *future* lifestyle goal have been cited by students as acute stressors (Jacobsen and Nørup, 2020, 257).

Personal relationships and family troubles are also prevalent reasons for seeking support (Golinger, 1991), however whilst having family support is associated with lower levels of stress (Byrom et al., 2020), the extent to which the student has additional responsibilities and may themselves be the main support provider for their family should be considered as students with childcare needs also look for wellbeing support and guidance (Briggs et al, 2012). Webb et al, (1998) found the highest rates of anxiety and depression in mature, female students, the majority of whom, it was suggested, had ‘domestic responsibilities’ (Webb et al., 1998, 924) although it is unclear how the researchers came to this conclusion given it was not a characteristic they measured in their correlation and is only suggested in the conclusion. Research exists asserting differential student experiences for those with responsibilities such as childcare and pregnancy (Manze, Watnick and Freudenberg, 2021). Despite the growing agenda to increase HE participation in the UK, there is an otherwise disappointing lack of recent academic consideration given to the demands of childcare for British parents studying at university within the literature (Thomas, Talbot and Briggs, 2021). Childcare is disappointingly overlooked or considered to be irrelevant to students; 'Because of their life-stage, students' close relationships may be relatively transient and unencumbered by children and other social commitments.' (Andrews and Wilding, 2004). Whilst the topic is explored in other settings such as Israel (Ben-David, 2021), Iran (Moghadam et al., 2017) and Ghana (Esia-Donkoh, 2014), few recent UK articles explore the MHW experiences of student mothers and even fewer of student fathers. Shobiye (2022) explored the relationship and intersectionality between wellbeing, financial stability and HE within the female refugee community in Wales; many of the difficulties cited are however applicable to mothers in non-refugee settings (Shobiye, 2022).

Despite individual pressures, the extent to which students can leverage their social capital and feel part of the university community is argued to be a key factor of their university experience and ultimate success (Tinto, 1997). "Sense of belonging" was included as a variable within the Larcombe, Baik and Finch (2022) study as part of the "course experiences" category and was found to be significant ($p < 0.001$) in predicting depression, anxiety and stress in all three cases.

2.2.3.4. Previous experiences of mental health issues, Personality and Metacognitive factors

There is evidence to suggest that those who have encountered a period of anxiety or depression are more at risk of recurrence with this being a particularly relevant factor for young people in a transition period between adolescence and adulthood (Lewinsohn et al., 1993; Rao et al., 1999). 22.7% of participants in a New Zealand study reported two or more episodes of major depression between 16-21 years of age suggesting students in this age bracket such as undergraduates are more at risk of recurrence (Fergusson et al., 2007). Furthermore, previous engagement with mental health services may in turn then influence the extent to which students are likely to seek help again, particularly if they found the service to be inadequate, increasing not only the risk of poor mental health but of failure to disclose (Martin, 2010; Venville, Street and Fossey, 2014).

It has been found that students approach the many decision points within university life affectively rather than strategically (Taylor and Harris-Evans, 2018) and their ability to effectively cope with such stressors is linked to their psychological wellbeing (Julal, 2013). Their decisions are increasingly emergent and associated with their individual psychological capital such that efficacy, hope, optimism and resilience "may help balance the demands and challenges of academic life or at least allow students to appraise them as more manageable" (Martínez et al., 2019, 1059).

This emphasis on the students' need for psychological assets can generate unhelpful deficit discourse on students' academic preparedness defined as the 'input quality of students' and 'the extent to which they are ready to study at HE level' (Thomas, 2002). University degrees require a great deal of personal investment in terms of time, cost and effort and students' ability to deploy 'coping mechanisms' at stress points is a key differentiator for success (Monk, 2004). Such pressures have been further exacerbated by the recent impact that the Covid-19 pandemic has had on the student experience (Watermeyer et al., 2021) and the need for students to demonstrate 'grit' and resilience (Crick, Prickett and Walters, 2021). Chow et al. (2018) reported a significant correlation between resilience and perceived student wellbeing in their subject-specific cohort with differences between postgraduates and undergraduates also identified.

2.2.4. Barriers to identification and disclosure of need and engagement with support

There is evidence to suggest that university mental health services deliver effective support for students who use them (Martin, 2010; Connell et al., 2018) and have been found to be an integral part of the solution process for those with a reflective style of problem-solving (Julal, 2013). However, despite the efficacy of university MHW services, there are many documented factors, out with the known risk factors, which influence students' engagement with them (Li, Dorstyn and Denson, 2014). Broadly the challenges identified can be summarised as; students acknowledging that that they have a support need (Aleven and Koedinger, 2000), awareness of the services available (Yorgason, Linville, and Zitzman, 2008) and propensity to seek help (Quinn et al. 2009).

Simon Wessely, former president of the Royal College of Psychiatrists, suggested that "We don't need people to be more aware. We can't deal with the ones who already are aware." (cited in Arie, 2017). Given that the 2016 YouGov survey found that 14% of students were unaware of any services available to them (Smith, 2016), which is consistent with the wider literature (Yorgason, Linville, and Zitzman, 2008), there is still more which can be done which Wessely fails to acknowledge. Students report that they would like more information about mental health and feel there is a need to demystify it as part of an awareness-raising programme (see Quinn et al, 2009, for an in-depth qualitative study with 12 students); as such a more appropriate suggestion, perhaps, is that lack of service awareness for students is not the *sole* cause of the problem and campaigns raising awareness raising should also consider the challenges already within services to meet existing demand in the population (see recommendation 5 in The British Psychological Society, 2021). Population level awareness is important, however Aleven and Koedinger argue that 'Recognizing the need for help is a (metacognitive) skill in its own right.' (2000, 293) and therefore direct-to-student campaigns tailored to circumstances may prove effective should there be a method of doing so.

One of the key challenges associated with supporting students, who have a diagnosis or have acknowledged their symptoms, is their failure to then disclose it to their institution due to stigma (Hunt and Eisenberg, 2010; Martin, 2010; Student Minds, 2017). Although Thorley (2017) reports that there has been a fivefold increase in the number of UK students disclosing a mental health condition over a ten-year period, the same report also details that just under half of those students, choose to share that information to their university (Thorley, 2017, 3-4). Stigma is a ‘powerful force in preventing university students with mental health difficulties from gaining access to appropriate support’ (Martin, 2010, 259) and impacts subsets of the population differently. For example, amongst international students there is a stigma of reporting MHW problems (Royal College of Psychiatrists, 2021) and heightened senses of loneliness (OfS, 2022); furthermore, young men have different perceptions of how to manage their negative wellbeing feelings and are less likely to disclose (Hope et al., 2005). The impact that demographics factors such as gender can have on help-seeking behaviour is complex. Considering gender alone some studies report significant differences (Eisenberg et al., 2007) and others not (Julal, 2015); studies exploring the intersectionality of race and gender have evidenced a gap (Lal et al., 2021; Shobiye, 2022) which emphasises the need for whole student views of students rather than considering factors in isolation. The importance of confronting intersectionality features heavily in the University Mental Health Charter (Hughes and Spanner, 2019) and studies offering a nuanced understanding of the challenges that student subpopulations face (e.g., King, et al., 2017; Danowitz and Beddoes, 2022; Peterson and Saia, 2022) offer the best chance of moving away from a one size fits all approach.

In addition to barriers to disclosure, there are also barriers to using services such as a perceived lack of privacy and time (Givens and Tija, 2002; Yorgason, Linville, and Zitzman, 2008), perceived long wait queues (Royal College of Psychiatrists, 2021; Batchelor et al., 2020; Priestley et al., 2021) and a sense that stress during university is ‘normal’ and will likely get better (Eisenberg, Golberstein, and Gollust, 2007). Whilst there is little research suggesting the demographic, psychological or situational factors influencing awareness of university MHW services, risk factors, which have been identified which correlate and predict mental health outcomes, may also influence help-seeking behaviour (Aldalaykeh, Al-Hammouri and Rababah, 2019).

2.2.5. Meeting the needs of students

Universities are complex organisational structures, therefore identifying the problem and the need for support is not enough; to meet students' needs there are still complex challenges to overcome (Mowbray et al., 2006). Furthermore, it shouldn't be assumed that just connecting a student with the right team will automatically solve the problem; there is a large amount of work to undertake to realise improved mental health outcomes (Banks, 2018). Nevertheless, signposting and referral is a step in the right direction (Thorley, 2017). This is particularly important given that ongoing pressures within the National Health Service are argued to be exacerbating demand for university counselling and support services (Brown, 2016).

Despite the clearly evident need for robust interventions to handle disclosure quickly and efficiently, it has been asserted that universities should not rely on reactivity. University leader, Sir Anthony Seldon, calls this an 'obsession' with reactive policy and advocates for preventative measures (cited in Coughlan, 2018). Whilst attempts to proactively increase levels of help seeking may seem unrealistic at a time when teams are already stretched due to demand, the call for prevention, proactivity and turning theory into practice is echoed in the mental health charter (Hughes and Spanner, 2019).

A key prevention strategy in healthcare is education as it builds awareness and skills simultaneously (Durlak, 1997). Examples in the literature include mindfulness training to reduce levels of stress and burnout amongst students (de Vibe et al. 2013), mental health first aid (El-Den et al., 2020) and workshops which has been found to be effective in reducing stress, anxiety and depression amongst students (see systematic review conducted by McConville, McAleer and Hahne, 2017). Solhaug et al. (2019) found that the effects of education and training persisted longitudinally (over a four-year period) and resulted in reduced rates of mental distress and improved problem-focussed coping however they also reported that their intervention did not have even a short-term impact on support seeking behaviour (Solhaug et al., 2019).

A systematic review noted that communication technologies were a promising medium for mental health prevention strategies but found that a serious limitation of expanding campus-based prevention activities was the lack of reliable data (Breet et al., 2021). The OFS openly promoted the need to support student wellbeing 'with the provision of clear, accessible and timely communications'[7] (OfS, 30 April 2020) during the Covid-19 pandemic.

An example of preventative mental health and wellbeing support which blends together education and communication is an online community which facilitated anonymous peer discussion boards for support and education (Richards and Tangney, 2008). Lattie et al. (2019) found that such digital mental health interventions can be particularly effective for the student population. Furthermore, studies which review the efficacy of student mental health interventions call for more information on 'student subsets' (Harrer et al., 2019, 1) to better understand differential rates of impact for those with 'risk factors' or 'preselected criteria'. This study suggests that their systematic review of student mental health literature found no significant impact for internet interventions targeting student wellbeing (Harrer et al., 2019, 14). This is contrary to Lattie et al. (2019) and the finding is treated with caution as the systematic review separated interventions targeted at wellbeing (n = 4) from other discrete mental health disorders such as stress, anxiety and depression (n = 76) which were shown to have positive intervention outcomes. As such Harrer et al. (2019) do evidence the positive impact of internet-based interventions but find differential rates of impact based on the severity of the condition on a spectrum of mental health which should be noted for population level approaches.

Staff recognise the importance of a whole university approach to student wellbeing by being equipped with appropriate support materials to manage students' needs, receiving appropriate training and having correct organisational structures in place (Mowbray et al., 2006; Cage et al, 2021, Martin, 2010, 272; Chadha et al., 2020). Whilst

[7] Office for Students Covid-19 briefing note, available at https://www.officeforstudents.org.uk/publications/coronavirus-briefing-note-supporting-student-mental-health/#generalpopulation, accessed on 18/07/2022

the ability to contribute to student support initiatives may be clear for professional staff in relevant roles, this responsibility may not be as clear for academic staff operating in various roles such as academic or personal tutors (Earwaker, 1992). Despite this, staff engagement with training for developing tutoring capabilities has been found to be low (Grant, 2006) which Walker (2018) suggests may be attributable to staff uncertainty over the level of responsibility involved in pastoral care (Walker, 2018).

Furthermore, it has however been speculated that constraints placed on staff by modern university institutions lead to a 'loss experience' for students (Scanlon et al., 2007) and that a lack of support for academic staff wellbeing has a direct impact on their support for students (Brewster et al., 2022). Certainly the philosophy of a whole university approach places emphasis on the wellbeing of staff as well as students (UUK, 2020), however, regardless of the challenges placed on university teams for adequate service allocation and design, discourse which suggests any causality between lack of staff resource and student mental health should be challenged. Both assertions from Scanlon et al. (2007) and Brewster er al. (2022) are unproven, ignore the wider context of poorer mental health for young adults (as explored in the previous section), underestimate the impact that preventative steps can take in promoting health and wellbeing (Martin, 2010) and oversimplify the specialist support needed for severe episodes of mental ill health. They also assume that the way resources are being utilised currently is efficient. As with any organisation, university resources are limited and research has already identified the opportunities for improvement including a review of workload allocation (Chadha et al, 2020; Mowbray et al., 2006; Cage et al, 2021). For example, one study has found that delays in completing mental health referrals are caused by staff having to spend more time gathering health information (Wang et al, 2004); this is important given research suggesting that long delays between diagnosis and treatment is a further barrier to help seeking (Zuriff, 2000; Hunt and Eisenberg, 2010). What both Scanlon et al. (2007) and Brewster et al. (2022) do highlight is the importance of appropriately supporting staff to better support students within an appropriate organisational structure of roles and responsibilities; this was recognised as essential to the success of a health promoting university (Grossman and

Scala, 1993). This in turn highlights that a whole university approach to student mental health requires a methodology which facilitates an approach to positively informing strategies to alleviate resource constraints. Brown suggests that the World Health Organisation model for support (World_Health_Organisation, 2009) could be adapted for student mental health support (Brown, 2018); with Level 1 (tailored self care) through to Level 5 (External specialist support) representing a hierarchy of need and intervention however a model of allocating students to a level is not discussed.

The Stepchange framework (UUK, 2020) stipulates the importance of making clear the roles, responsibilities and boundaries for staff in any mental health activity and equipping staff with meaningful data and information represents an opportunity for improved student support (Barkham et al., 2019; Hughes and Spanner, 2019; UUK, 2020). Attempts to provide practitioners with data include giving them more information in advance of therapy sessions to reduce known delays in the therapy process finding that staff appreciate the extra time it allows them in sessions (Wang et al., 2004). Similarly, it has been found that giving student mental health information to therapists prior to their therapy enabled staff to feel better prepared for the sessions (Kim et al., 2011). In both Wang et al. (2004) and Kim et al. (2011) the information provided to practitioners was personal health information and the efficiencies represented a digital tool to capture patient history and symptoms in advance of service delivery; it is not clear what the scope of the data gathered and presented was in addition to health i.e. it is likely (but not explicit) that they captured demographic information such as age and gender. Kim et al. (2011) discuss capturing log data from the system itself but again it is not clear whether this was presented to staff as part of a user profile or just as contextual information.

2.3. Using data to target and personalise student mental health support

Approaches enabled by data and technology are considered to be particularly useful to improving our understanding of population level need and designing support interventions at scale (UUK, 2015; UUK 2018; Thorley, 2017; Office for Students, 2019). In his recommendation for a range of underpinning common principles to whole university approaches, Thorley includes (i) 'robust data and evidence', (ii) 'prevention and promotion', (iii) 'early intervention and low-level support' and (iv) 'responding to risk, and crisis management' (Thorley, 2017, 68). This section reviews how data can be used by university teams to support students through the lens of "targeted" and "personalised" student support activities.

2.3.1. The rationale for targeted and personalised support

> "It is a truism of health education that programs and interventions will be more effective when they are culturally appropriate for the populations they serve. In practice, however, the strategies used to achieve cultural appropriateness vary widely" (Kreuter et al., 2003, 133)

Targeting and personalisation strategies assume that populations are heterogenous and that homogenous subpopulations can, through analysis, be identified based on grouping like characteristics. These are, in effect, the 'student subsets' for which Harrer et al. (2019) argue may maximise the effectiveness of targeted interventions. When defining targeting, some start by identifying a subgroup so that a new program can then be designed to meet their specific needs rather than that of the population (e.g., Pasick et al., 1996). Traditional marketing deployments favour terminology such as 'narrowcasting' (Rimal and Adkins, 2001) for specific proactive communication with subgroups. 'Audience segmentation' (ibid) is therefore the process of grouping consumers by like characteristics and 'targeting' is the mode by which the product or intervention is delivered e.g., email. Thus, communication strategies can be designed to segment and target specific audiences for new services, but may also emphasise utilisation of existing services too, and with the following goals; (i) 'enhancing cognitive preconditions for message processing' and (ii) 'enhancing message impact through modifying behavioural determinants of goal outcomes' (Hawkins et al., 2008, 454).

Personalisation, or 'tailoring' (van der Hof and Prins, 2008), is the act of using information about the target population to present interventions as being highly relevant, applicable or individualised and attempt to increase adoption (Hawkins et al., 2008). From an HE perspective, one of the key messages from the OFS is "It's all about personalisation" (OfS, 2018a, 5); specifically, they suggest that 'Any solution has to be personalised to the individual's circumstances and information needs if it is to be helpful'(ibid).

Whilst personalisation strategies may operate with benign intentions, they do so by influencing the emotions and perceptions of their audience (Hawkins et al, 2008). As such it's essential to question their nature from an ethical perspective. Kreuter et al. (2003) explored 'cultural appropriateness' with respect to tailored health interventions; their work suggests that the process of personalising content to targeted groups may improve the acceptance and adoption of interventions but that key challenges exist at the outset. The first challenge is that the culture of the group is often 'assumed rather than assessed' (ibid, 134) and that proxies replace the actual measurement of a groups' needs; defining the characteristics of a group within the parameters of what you know about them is therefore difficult. The second challenge is that, depending on the specificity of characteristic-driven grouping, it could result in an impractical number of subpopulations; very large populations may be simple to identify and target but hard to achieve high relevance across the group and very small subgroups may offer high levels of relevance but may take considerable effort and time to develop. Finally, they suggest that a methodology or understanding is required to prioritize between multiple groups requiring intervention, particularly when individuals exhibit multiple characteristics and can therefore be a member of more than one subgroup. Big data, which is the accumulation, from digital traces, of personal information (Michael and Lupton, 2016), is seen as a particularly powerful approach to facilitating high volume activities such as targeting and personalisation at the population level (Wamba et al., 2015).

2.3.2. Data and technology for targeted and personalised support

There has been an 'intensification and spread of data analytics' (Beer, 201721) due to advancements in technologies designed to exploit increasing volumes of data capital. Systems are now capable of storing more data due to cloud technologies and, as with any capitalist asset, the more volume and/or quality, the better. Using data is often equated to improved business efficiency where processes are faster, cheaper or better by some local definition of success (Gandomi and Haider, 2015). This has been summarised as the Vs of big data: Volume, Variety, Veracity, Velocity and Value (ibid; Anshari et al., 2019). Furthermore, given the size and scale of population level datasets, analytics technologies are increasingly used in conjunction with big data to achieve these aims. The perceived speed with which practice can operate is a particular advantage; "Slowness, it would seem, is equated with wastefulness. The slowness of non-data-informed practices is contrasted to the lightning speed of data analytics. Analytics are presented as solutions to slowness" (Beer, 2017, 27).

As the popularity of analytics-based, targeted and personalised approaches grows in commercial sectors, so too has it grown within university settings (Daniel, 2015). Research attempting to target and personalise student wellbeing support are limited however there are many examples where this strategy has been used for wider student success outcomes such as retention and engagement (Foster and Francis, 2019; Francis et al. 2019). The remainder of this section reviews specific HE case studies and considers how data and technology play an enabling role in targeted and personalised approaches to student MHW in university settings.

It has been found that navigating the university's support structure to connect with an appropriate resource is something students often find challenging (Priestley et al., 2021). To facilitate this, many universities have restructured and consolidated their services for ease of use (UUK, 2015) and an important aspect of this is the use of digital tools to better present support options and streamline referral via cross-team data sharing for personalised triage (Priestley et al., 2021). Mills argues that, as data availability increases so too do the opportunities for personalization, moving away from a 'one size fits all' approach that is incompatible with a heterogenous population (Mills, 2022). This is considered as an enabler for data and evidence to drive early intervention (Thorley, 2017; Royal College of Psychiatrists, 2021). Furthermore, to create highly relevant campaigns for students, there is a need to understand more about their recent experiences which highlights the importance of data 'freshness'

(Fritsch, 2008).

Increasing the availability of digital tools is seen as one option to alleviate the demand on university counsellors, especially where staff to student ratios are in excess of international guidelines (Stallman, 2012). Richards and Tangney (2007) explored this concept via the design of an informal online community which they argued provided scalability and addressed the differential propensities of certain populations such as young men to avoid face to face support. Broadbent (2020) details a digital tool, 'Intelligent Agent' (IA) which allows academic staff to "target behaviours and outcomes" using "semi-personalised" automated email messages (p.4). To facilitate the approach, Broadbent describes the process of pre-determining the criteria which the IA will automatically apply e.g. "Not logging in to the LMS (Learning Management System)" along with the timeline which the IA is programmed to follow e.g., send low LMS email in Week4. The impact that this tool had was positive but the study warns that overuse or overreliance may diminish this impact.

An approach of particular interest is 'nudging' (Reisch and Sunstein, 2016; Fritz, 2017; Blumenstein et al., 2018). Nudges are communications designed to guide people in certain directions whilst seemingly preserving their freedom of choice (Reisch and Sunstein, 2016). Nudges are often underpinned by data to understand and target audience (Blumenstein et al., 2018). Whilst Walton (2014) positions such approaches as 'The New Science of Wise Psychological Interventions' others suggest that nudging is more of an 'art form' whereby the 'nudger' must balance strategy with sensitivity to effect positive, enduring change for students (Brown et al., 2022, 1). As nudges embrace personalisation, they aim to be more relevant and impactful to their audience; targeting and personalisation in nudges therefore allow specificity of choice and its delivery (Mills, 2022) which, in the case of student support nudges, may represent the difference between a student engaging with resources or not (Brown et al., 2022).

An example of nudging students in the literature is Dart and Spratt's (2021) personalised email programme which was designed to improve learning opportunities within two mathematics courses. Dart and Spratt discuss the idea of 'at risk' students and applied 'if then' rules to raw data to identify engagement and academic risk factors (test scores and VLE activity) which were subsequently used to prescribe the intervention, and tailor its relevance. It was successful in terms of improving course satisfaction amongst the students who received a personalised email compared to the control group who received generic support. Similarly Plak, van Klaveren, and Cornelisz used a control group approach to measure the impact of their email nudge programme on effecting the desired behaviour among students however this study reported no significant effect on driving student engagement and explains the complex relationship between defining the target behaviour and its theoretical relationship with the target outcome (Plak, van Klaveren, and Cornelisz, 2022). Banks (2018) used a targeted email approach but rather than it being the intervention itself, it acted as a segmentation mechanism to evaluate a mental health intervention designed specifically for students of Colour. Not only was the email described as a targeted approach, the intervention, which placed a therapist of Colour in an existing team tasked with confronting intersectional challenges such as disability and gender, was also described as being an attempt to engage with 'target populations'. This approach relied on students self-selecting whether they identified as a person of Colour.

These examples are part of a small, but growing, evidence base for nudge analytics as a tool for positively influencing traditional student success outcomes such as engagement and continuation (Frankfort et al., 2012; Tabunca et al., 2015; Damgaard, and Nielsen, 2018; Dart and Spratt, 2021; Brown et al., 2022; Plak, van Klaveren, and Cornelisz, 2022) however there are no examples of using data-based nudging for improved student mental health outcomes. Reflections on approaches to alternative student outcomes have suggested that there is scope for its inclusion within a wider scope of support (Blumenstein, 2020).

As the personalised and targeted nudging approach continues to influence UK education policy (Bradbury et al., 2013) important concepts are raised for translating theory into practice including, again, the importance of considering roles and responsibilities for nudging (Brown et al., 2022). A particular assertion relates to the balance between being able to identify students for support (requiring technical, data leveraging skills) and actually delivering targeted and personalised interventions is the juxtaposition (requiring a level of sensitivity and pastoral care) (Brown et al., 2022) which may not be mutually inclusive to one role. Returning to Dart and Spratt's (2021) example of personalised emails, this paper explains the process of taking raw student data, applying an algorithm, or an 'if, then' rule as they describe it, and turning this information into a personalised email campaign for mathematics students (see Figure 1 on page 6 for a visual of how this was achieved in their study). This highlights the complexity and level of manual intervention required to segment the population and this example was only one cohort of mathematics students; at a whole university level the volume and complexity of the data increases. To remove the complexity of gathering, hosting and the subsequent algorithmic analysis of student level data, commercial tools have emerged (see Appendix 1a for examples).

The common theme throughout these platforms is the commercialisation of personalisation however it isn't always clear how this is to be achieved nor the level of agency required by staff to run ad hoc campaigns for signposting support using such tools. The platforms appear to take on the heavy lifting of student data via algorithmic, digital processing delivered as software as a service (SaaS) via web-based browsers therefore the need for data and technical skills to which Brown et al. (2022) alludes may be mitigated. As such they are designed for ease of use and to maximise the staff experience which is part of their commercial attractiveness or "USP (Unique Selling Point)" (unique selling point) however, as with any commercial platform, there is an introduction of a third party into the university/ student data relationship which fuels the counternarratives of platform capitalism (Pasquale, 2016) vis-à-vis privacy and control (Srnicek, 2017).

The next section reviews the use of data clustering and profiling as a method for achieving targeted and personalised student support; due to the limited deployment of these applications within university settings for the specific purpose of improved mental health, a wider scope of literature is reviewed to understand the opportunities and challenges that this approach may have in the specific context of university students' MHW.

2.4. Profiling for intervention and service design

As outlined in the previous section, data and technology can be used to target and personalise student mental health and wellbeing support in university settings by using known risk factors to group students which are then subsequently used to intervene. Another name for this type of grouping activity may be 'profiling' which is not currently prevalent in HE research or practice despite it being a popular approach in many other disciplines and practices (Durvasula, Lysonski, and Andrews, 1993) including healthcare (Eskes, et al., 2016; Lin et al., 2017), business and marketing (Zarantonello and Schmitt, 2010), and criminology (Turco, 1990; Godwin, 2002). This section begins with an attempt to define profiling (2.4.1) based on existing literature before analysing the two key challenges with regards to using profiling to target and personalise student mental health interventions. As profiling is not a segmentation methodology in its own right, section 2.4.2 considers quantitative and qualitative methodologies which have been used to date. Profiling also has sociocultural implications when mediated via data and algorithms (Cheyney-Lippold, 2017) rather than the traditional human-led decision making. As such these implications or 'algorithmic identities' (Bharti, 2022) are explored in section 2.4.3.

2.4.1. Defining profiling

It should be noted that 'profiling' as a term can be applied to a variety of scenarios which are not applicable to the present study including the use of profiling to analyse digital resources (Zaparanuks and Hauswirth, 2012) and improve the performance of computer programs (see Anderson et al., 1997). In biology, DNA and gene profiling is a popular method to monitor, predict health outcomes e.g. to better understand the development of cancers (Reis-Filho and Pusztai, 2011). Furthermore, the use of 'profiling' is extensive and well developed in the field of criminology, where the definitions are invariably grounded within the concept of profiling to better understand 'the offender' (see Egger's Psychological profiling: Past, present, and future, 1999). Whilst the profiling method may share similarities, the connotations of offence for conceptualising individual student behaviours is inappropriate and skewed towards risk. A whole university approach to improving student mental health, across the spectrum of both positive and negative health outcomes, requires a definition which operates at population level. For the purpose of this review, profiling is examined with respect to approaches aiming to better understand the human social experience based on the scientific analysis of subject-level observations pioneered by Freud (1933).

Despite the interdisciplinary differences, there are useful learnings from the field of criminology which help frame profiling for student mental health. Bartol and Bartol (2012) consider the difference between case-focussed deductive profiling which begins with an outcome and works backwards (e.g. student has low mental health because they did not seek help at the right time) and, inductive profiling, which uses statistical averages to infer typical characteristics (e.g. young male students exhibiting certain risky behaviours may suffer poor mental health now or shortly in the future). Profiles may be used to understand behaviour just as equally as they may be used to effect it (Durvasula, Lysonski, and Andrews, 1993) however, with inductive profiling specifically, there is an inherent relationship with the ability to predict outcomes as a result of the new knowledge inferred via the new profiles e.g. predicting the energy usage of an apartment block based on profiles of when and how residents occupy a building (Barthelmes et al., 2018). Kleinberg et al. (2019) suggest that 'The whole idea of prediction is sometimes viewed as objectionable because it has the flavour of profiling' (Kleinerg et al., 2019, 136) which hints towards the challenge of social acceptance with which profiling may be associated, particularly in relation to algorithmic decision making (ibid). Indeed, the subsequent intervention on a prediction can be interpreted as 'behavioural modification' (Ruckenstein and Granroth, 2019) which has agentic implications, particularly where the algorithm is opaque or imposes an intervention on a subject (see 2.4.3).

The collection of works entitled *Profiling the European Citizen* (Hildebrandt and Gutwirth, 2008) offers much to the discussion of profiling across multiple disciplines; therein Hildebrandt (2008) offers the following definition of profiling;

> 'The process of 'discovering' correlations between data in databases that can be used to identify and represent a human or nonhuman subject (individual or group) and/or the application of profiles (sets of correlated data) to individuate and represent a subject or to identify a subject as a member of a group or category (Hildebrandt, 2008, 19)

This process aligns to Bartol and Bartol's (2012) inductive profiling definition but lacks the predictive or at least, action-enabling element which is core to the translation of new knowledge about a population into action. Profiling to improve student mental health outcomes requires that profiles are actionable in some definable way otherwise they may be considered purposeless. Therefore, the definition for a student profile below (abridged from the original), which considers both present and future states, is preferred for the scope of this work;

> 'A student profile represents a structure containing both direct and indirect information about a student [...] The main interests of profile modelling are the prediction domain and decision support. Indeed, profile modelling allows the discovery of patterns of profile that can be used for similar cases and this fact facilitates research and makes more efficient systems centered on the user' (Hamim, Benabbou and Sael, 2019, 1-2)

This suggests that profiling can be a useful approach to assist with identifying categories of students and, importantly, emphasises how they may be used by university teams to improve decision support. In this sense profiling can be aligned to the improvement of students' 'choice architecture' (Sunstein, 2008) relating to MHW support. Profiles may be utilised either to target mental health campaigns at certain subgroups or assess characteristics which could be factored into the personalisation (and therefore assumed improvement) of systems and support. The next section considers examples where this has been attempted.

2.4.2. Methodologies for profiling mental health

Whilst 'profiling' describes a deliberate logical grouping process and 'profiles' denote the outputs of such, neither constitute the methodology for creating subgroups from a given population. Grouping can be achieved via many approaches, not all of them quantitative or technological. This section considers existing approaches to profiling students within university settings.

Beginning with a review of quantitative approaches, a notable contribution to the idea of profiling students is the use of 'fuzzy models' to create a student profiling system which used digital learning data to produce personalised learning plans (Xu, Wang, and Su, 2002). The results of the study suggested that the personalisation functionality, which was delivered after profiling students' time-based reading activity had taken place, led to a comparatively better outcome for students. Specifically, whilst the focus was on learning outcomes rather than health, this study linked profile based personalisation (in this case emails, quizzes and advice) to improving motivation in an educational setting with promising results. There exists however a number of issues with this paper including a lack of specificity around exactly what outcomes were measured and the theory of change vis-à-vis how profiles influenced the personalisation of contact, what had been in place before this intervention and what value the profiling added to the process.

Understanding the theory of change between profile creation and intervention is crucial to enacting meaningful change in the desired outcomes; this includes conscious design at the independent variables stage as these are the proxies for behaviour (Canhoto and Backhouse, 2008). For example, Foster (2020) sought to understand why students engage with their own learning engagement data via a personalised digital smartphone application and used profiles to group user behaviours based on logins to consider nuance within the emerging theory of change. It found that some students will engage with it for better self-management and organisation whereas others are more likely to seek signposting and self-help opportunities concluding that understanding the different user profiles can then influence future development strategies for such technology. The quantitative methodology for creating profiles was part of an overarching mixed methods approach utilising critical realist grounded theory to better understand students' perceptions of such activities qualitatively. It's argued that the profile and the theory for its use, support the intervention agent (in that case, the student) to better support their decision making. Similarly Lin et al.'s study on risk-based analytics within healthcare settings (Lin et al., 2017) utilised a Bayesian multitask learning (BMTL) model to derive risk-based profiles and used this to highlight the practical implications of such an approach to support both personalised and preventative care agendas. Again, the argument extends beyond the creation of profiles to how they act as decision support tools, in this case supporting the physician at the point of care; as such there is a strong argument to suggest that profiling for health support is as equally applicable in university settings as it is in traditional environments of patient care.

When seeking a methodology to group students in profile-like segments, it becomes clear that an approach which may be used within a mixed methodology might be advantageous. 'Clustering' typically looks to satisfy one (or more) of three aims: data exploration, hypotheses testing or research validation (Huberty, Jordan and Brandt, 2005). Cluster-driven profiles have been explored in relation to students' academic performance (Shovon and Haque, 2012), learning style (Kyndt et al., 2012), geographic background (Boscaino, Sottile, and Adelfio, 2020), and goal-orientation (Dina and Efklides, 2009). A study by El Ansari et al. (2011) administered a questionnaire and used the resulting data to create 'profiles' from 'clusters'. The authors argue that these student mental health profiles should be university-specific and localised as part of a health promoting university framework and that these profiles can be utilised to promote healthy behaviours. Whilst this study makes some useful recommendations about the need for continual, longitudinal monitoring, both the clustering and profiling methodology in this study are very weak. There is no discussion of the clustering mechanism or the decisions taken in that process and therefore the translation of clusters to profiles relies solely on the reader interpreting the statistical results as being wholly representative of an exclusive student profile.

Furthermore, clustering approaches for student mental health are not prevalent. A systematic search of multiple databases yields only 11 results when searching for the following terms within the abstract: “mental”, ”health”, “analytics”, “cluster”. Including the term “student” reduces the results to zero indicating that this space is ripe for research. Appendix 1 includes a summary of each article and highlights that the majority of the empirical studies dealing with the mental health of human participants started with a sub-population of those in the higher categories of risk; as such there is a clear focus on identifying the traits of those with poor mental health to prioritise reactive interventions rather than a drive to understand the mental health outcomes for all. A further observation of the literature reviewed is that the majority of cluster analyses on mental health utilise static datasets; those which do consider mental health longitudinally (Burt et al., 2004; Starks et al., 2010) offer insight into the longevity of profiles which is an important consideration when considering the relevancy of interventions over a sustained period of time.

The average amount of clusters identified in the mental health cluster analyses reviewed is 3.7; this represents the real opportunities for SMHP in practice and the need for research to inform its operation. Rather than directing mental health interventions at one homogenous group there’s the possibility of targeting three or four tailored interventions to the student body however no ‘whole university’ approaches to identifying student profiles have been developed. Broglia et al. (2021) pooled data from four UK university intervention services to measure the efficacy of counselling; one of the aims of the study was to ‘profile student mental health issues and presenting conditions from a small cluster of HE counselling services that used different outcome measures’ (Broglia et al., 2021, 3). This represents a recent trajectory in this space with scope for further enquiry.

2.4.3. Ethical considerations relating to profiling to enable targeted and personalised support: Lessons from Learning Analytics

Organisations in all sectors are driving personalisation agendas by using big data and analytics to tailor and nuance customer experiences (Grover et al., 2018); profiling is an increasingly popular approach to achieve this (Hildebrandt and Gutwirth, 2008). In addition, to facilitate the mediation of data-driven insights into practice, digital platforms have emerged; for some, digital and algorithmic platforms stand at the centre of economic and cultural modern life (Mackenzie, 2018) yet not without strong critical analysis of its implications for categorization, control and privacy (Cheney-Lippold, 2017). The growth in popularity of targeting services at groups has been criticised as everyday surveillance (Lyon, 2002; Henman 2004, Ruckenstein and Granroth, 2019). Yet, communication, such as personalised emails and nudges can be a vehicle for supporting students' decision making (Thaler and Sunstein, 2008; Mills, 2022). There is a tripartite tension between supporting, influencing and controlling decisions associated with policies which embrace behavioural economics. Such approaches may 'exteriorise' choices (Bradburv et al., 2013, 258), placing more emphasis on behaviour and less on the individuals' needs. This, Bradbury et al. argue, poses serious implications for educational policy. Sunstein pre-emptively acknowledges this key criticism as paternalism (Sunstein, 2013) suggesting such objections are not effective in stopping the growth in popularity of such methods:

> While some people invoke autonomy as an objection to paternalism, the strongest objections are welfarist in character. Official action may fail to respect heterogeneity, may diminish learning and self-help, may be subject to pressures from self-interested private groups (the problem of "behavioral public choice"), and may reflect the same errors that ordinary people make. (Sunstein, 2013, 2).

In an HE context, 'platformisation' refers to Universities' investment in algorithmic, digital technologies to meet the needs of stakeholders in an increasingly marketized HE sector (Robertson, 2018; Williamson, 2019a; Decuypere, and Landri, 2021). Critics suggest that such approaches are part of a surveillance and monitoring agenda and techniques like profiling may have 'perverse consequences' (Williamson, 2019b, 1). The threat of losing autonomy and agency as described by Sunnstein is also prevalent in the counternarratives to platform capitalism developed by Pasquale (2016)(see Figure 1). Algorithmic profiles are argued to lead to 'loss of agency when serendipitous or unpredictable options are effectively hidden or obscured' (Pasquale, 2016, 311).

Narratives of Platform Capitalism

Conventional Narrative	Counternarrative[7]
Platforms promote fairer labor markets by enabling lower-cost entry into these markets by service providers.	Platforms entrench existing inequalities and promote precarity by reducing the bargaining power of workers and the stability of employment.
Platforms reduce the impact of discrimination by increasing the number of service providers in transportation, housing, and other markets.	Platforms increase discrimination by identifying customers with picture-based profiles which reveal their race or racially-identified names. Ranking and rating systems can also reinforce bias.
Regulators of platforms are likely to reflect the biases and interests of incumbent providers (like taxis and hotels) thanks to incumbents' political ties.	Large platforms now command so many resources that their own lobbying efforts can easily swamp those of fragmented and uncoordinated incumbents.
Large digital platforms have gained massive market share because of the quality of their service.	Large digital platforms have gained massive market share because of luck, first-mover advantage, network effects, lobbying, strategic lawlessness, and the unusually low cost of investment capital due to quantitative easing.
Platforms promote economic growth by drawing the un- and under-employed into the labor market.	Platforms undermine growth by reducing wages as workers scramble for gigs by offering to complete them for lower wages than their competitors.
Platforms promote flexibility by breaking down jobs into tasks, enabling workers to piece together work at their own pace.	Low-pay gigs and piecework force workers to be "ready for duty" constantly lest they miss an opportunity to work.
Using data-driven profiles of users, platforms can preemptively channel them to the workers they are most compatible with.	Users may experience loss of agency when serendipitous or unpredictable options are effectively hidden or obscured.

Figure 1 Pasquale, F. (2016). Two narratives of platform capitalism. Yale Law and Policy Review, 35, 309-320, 311

Improving student success outcomes has already been incorporated into a proactive digital intervention approach called 'learning analytics' (see Clow, 2013, for an overview of learning analytics). It aims to distil risk factors to individualised data points by using existing data. Some have hinted that there may be the opportunity for learning analytics to support the MHW of students (Ahern, 2018; Cormack and Reeve, 2022). It is suggested that, as these practices emerge within HE, it raises 'significant concerns regarding the trust students place in their institutions to use that data according to their expectations.' (Jones et al, 2020). With this in mind, research is now beginning to investigate a code of practice for the use of such approaches with respect to mental health and wellbeing (Cormack and Reeve, 2022).

Data analytics and profiling, even when applied to the improvement of students' engagement and wellbeing is often discussed within the discourse of surveillance (Williamson, 2019) based on its potential to marginalise groups (McKay and Devlin, 2016). Students have actually advocated for the intelligent use of their data, not only in identification of risk but also for the prescription of therapeutic intervention (Priestley et al., 2021). Sometimes referred to as the 'privacy paradox' (Tsai, Whitelock-Wainwright and Gaŝević, 2020), students have been found to trust their institution to use the data responsibly (Arnold and Sclater, 2017; Jones et al., 2020; Tsai, Whitelock-Wainwright, and Gaŝević, 2021). There is evidence to suggest that students' trust is 'differential' and their perceptions of using their data is influenced by whether it is being used for profit and an understanding of their institution's duty of care (Prinsloo and Sade, 2015; Arnold and Sclater, 2017). This suggests a spectrum of consumer concern which correlates to a similar spectrum of application where some uses of data analytics and algorithms are considered 'harder' e.g. those intended to govern and control or 'softer' e.g. those seeking a more intimate relationship with data (Savolainen and Ruckenstein, 2022).

From a practical perspective, there is concern from counselling staff that approaches like this can undermine their professional judgement and promise things to students that then can't be delivered (Tsai, Whitelock-Wainwright and Gaŝević, 2021). Zuriff (2000) argues that there is a risk of students feeling 'abandoned' when they are referred on after the first therapy session but also suggests that having this conversation *too* early can be even more disruptive to the support process; this suggests a balancing act or 'art' as Zuriff calls it between the practitioner accessing information and using it to change the course of the therapy process. Jones et al. (2020)

argue that in these situations, staff may suggest interventions driven more by predictive measures than students' needs however this is very much contrary to the clinical judgement which Zuriff suggests is core to student mental health practitioners (Zuriff, 2000). On this basis, we should be aware that counselling and practicing staff within university mental health teams are operating from a therapeutic and clinical background, therefore they have experiences and foci which may not be generalisable to the wider population of university workers (Zuriff, 2000).

Algorithms are argued to have plural meaning which blur the traditionally technical aspects of their entities with the non-technical facets of their creation, maintenance and application (Seaver, 2017; Bucher, 2018; Savolainen and Ruckenstein, 2022). As they become ever complex some speculate that not even their developers really understand them (LaFrance, 2015); this creates a hotbed for discussion on their role in society. Seaver argues, 'In this view, algorithms are not singular technical objects that enter into many different cultural interactions, but are rather unstable objects, culturally enacted by the practices people use to engage with them.' (Seaver, 2017, 5). Specifically, it is argued that power may be assumed through the 'claims' to which algorithms contribute (Bucher, 2018, 3), which delineates computable instructions from the Foucauldian understanding of 'power', 'knowledge' (Foucault, 1980) and 'discipline' (Foucault, 1975/1977) and, specifically, the extent to which such power can be used so that 'one may have a hold over others' bodies, not only so that they may do what one wishes, but so that they may operate as one wishes, with the techniques, the speed and the efficiency that one determines.' (Foucault, 1977,138).

Reviewing literature on algorithms presents a potentially threefold dilemma for SMHP. Firstly, there is a risk that algorithmic outputs are inaccurate or even 'offensive' (Bucher, 2018, 102) and capable of exacerbating existing inequalities (Kristensen and Ruckenstein, 2018) leading to mismatches which are problematic and influential to the agency and autonomy of the users of such profiles (e.g. counsellors or practitioners in university mental health teams) or even the students who have been profiled.

Consequently, and thus secondly, there is a danger of such outputs rendering university mental health practitioners into, as Foucault calls them, ‘docile bodies’ (Foucault, 1977) via the introduction of seemingly altruistic attempts at improving student mental health support. Schwan and Shapiro (2011) assert that Foucauldian docility ‘works on the smaller scale of individuals’ (Schwan and Shapiro, 2011, 99) rather than operating at the macro level of whole populations and relies on individuals being under constant supervision. In this sense supervision may mean via a superior e.g. manager or via clinical supervision which seeks to function as ‘quality control, maintaining and facilitating the supervisees’ competence and capability and helping supervisees to work effectively’ (Milne, 2007, 440, Table 1). Therefore docility, brought about by algorithmic profiling, may represent a harmful form of disciplined constraint for mental health teams which is at odds to the relationship-based form of supervision inherent in their practice which emphasises ‘empathy and warmth’ (ibid). Thirdly, Benasayag, in his book *The Tyranny of Algorithms* (2019/2021), suggests that early forms of algorithmic processing, *‘cybernetics’*, promised a rationality that is ‘consistent and conquering’ via the delegation of decision and control from the human to the machine (Benasayag, 2019/2021, 31). This further highlights the potential for algorithmic profiling to infringe on agency and autonomy but assumes that their power is derived through decisions independent to human control (Diakopoulos, 2015, 400) which fails to fully conceptualise the extent to which humans are intimate with algorithms as their designers and enactors who may ‘negotiate and re-negotiate’ their autonomy (Savolainen and Ruckenstein, 2022) to employ them benignly as would be required in SMHP. There is therefore a question of how the ratio of intimacy remains between those who design the algorithm, those who create the profiles and those who embed them in to personalised and targeted support for students.

2.5. Summary of literature reviewed

Whole university approaches to mental health are increasingly promoted by policymakers however there is little academic research to evidence how policy has been translated into effective, scalable practice. Whilst there are many small-scale approaches to quantitatively analysing student mental health (see 2.2.1), there are but few examples of large samples (relying on pooled data) and only limited deployment of the WHO-5 despite its validation (de Wit et al., 2007; Topp et al., 2015; Krieger, 2014).There are many other clinical and non-clinical tools available to capture mental health data yet it is clear that, in research contexts, measuring student wellbeing currently requires students to complete “surveys” or “screeners” to subjectively measure their MHW (2.2.2).

Research has identified student mental health risk factors (2.2.3) however it is often difficult to extrapolate causality. Furthermore there is little research into positive factors for mental health and little published on the applicability of risk factors at the positive end of the mental health spectrum. Moving beyond data to action, no research was found to have created mental health profiles for the purpose of targeted or personalised student support interventions despite policymakers driving an increasing digital agenda.

Increased data availability and analytical capabilities has been found to proliferate targeted and personalised approaches however not without connotations of what is sometimes referred to as ‘dataveillance’ (Clarke, 1994; Hildebrandt, 2008). Big data is used to create high levels of relevance (Henman, 2004; Nabeth, 2008) within service interactions and thus targeting and personalisation aims to influence human behaviour. This is argued to be pervasive in contemporary society (Zuboff, 2015), going beyond micro level marketing campaigns to the macro level ‘datafication’ of contemporary society (van Dijck, 2014).

Profiling has been explored and found to be a methodology for achieving the segmentation and stratification of groups (Hildebrandt and Gutwirth, 2008) however three key challenges were identified; (i) the possibility of inaccuracy, misrepresentation or exacerbation of existing challenges, (ii) the rendering of mental health teams as docile agents under restrictive supervision, and (iii) the level of intimacy achievable between university mental health staff and the algorithms used in the profiling process to retain control over its application to avoid harmful effects.

3. Methodology

3.1. Introduction

This chapter is an account of the research process from May 2021 to November 2021. The chapter begins with a brief but relevant declaration of the relationship between this research and a wider project commissioned by the Office for Students which focusses on the sector wide opportunities for Student Mental Health Analytics (Office for Students, 2018). This is followed by a section on the theoretical underpinnings of the research design, which is then explored in more detail relative to the methods and design.

3.1.1. Relationship to the Office for Students Project

In June 2019, a group of UK universities successfully bid for funding from the Office for Students (OfS) as part of a competition entitled "Achieving a step change in mental health outcomes for all students" (Office for Students, 2018). The project, led by Northumbria University in Newcastle, England, aims to research "how big data, technology, educational analytics and student facing interventions can be used to recognise and support students with mental health issues" (Northumbria University Press Release, 2019). As an employee of Northumbria University, co-writer of the original bid and active researcher in the deployment of analytics to improve the student experience, I was appointed to the Project Executive Board in 2019. In 2021, I then chose to undertake the current research as part of my existing doctoral programme at Lancaster University, to support the project strand on data analytics which aims to "identify actionable insights" (ibid) and "to deliver holistic approaches to student health, wellbeing and education" (ibid).

The first part of the analysis, the quantitative clustering to produce student mental health profiles, was conducted using data collected by the project rather than myself. During the second phase of the research I engaged with university support staff from Northumbria University who had varied pre-existing knowledge of the OfS project; some were also known to myself as former colleagues. There is the potential to consider this thesis under the category of institutional research (Zimmer, 1995) whereby data has been collected and analysed to inform institutional decision making on how to better support a whole university mental health agenda through strategic and operational deployment of SMHP. I would suggest that this is only partially the case in the sense that the data collected and analysed is part of an institutional project; however the ambition of this thesis is beyond institutional research (IR) with an aim to support student mental health across the sector. Nevertheless the risks arising from the elements resembling institutional research have been mitigated based on the suggestion the IR is fraught with methodological bias, operational risks or, as Watson terms them, 'traps' (Watson, 2009). This study has heeded the warnings and striven for reflective and responsible pragmatism rather than theoretical perfection (see Towards Reflective Practice in Watson and Maddison, 2005, 7).

3.2. Theoretical underpinnings of this research

3.2.1. Relativism

The aim of the research is to identify, investigate and validate student mental health profiles, created through an exploratory clustering approach, to understand the opportunities for University Support Services delivering targeted and personalised interventions. The primary purpose of this research is not to create a generalizable set of student mental health profiles which universities can use 'off the shelf' as part of new or existing mental health strategies. Naturally however the profiles may inspire immediate actions, particularly if they resonate with existing local challenges within an institution. Rather, the intention is to take an exploratory approach to identifying emerging quantitative themes and use these to create experimental student profiles with the purpose of testing the hypothesis that such an approach may be useful to those employed in the capacity of providing student mental health support. These aims have directly influenced my choice to underpin the current research with a relativist ontology which is explained in detail hereafter.

My previous research on the use of analytics in HE settings (Foster, 2020) utilised the transcendental concepts of Critical Realism (CR) (Bhaskhar, 1978). The overarching philosophy of Realism rejects the reductionist views of positivism and empiricism by offering a 'third way' between the two (Sayer, 2000) which I believe is essential in social science and educational research which aims to have an impact in a complex and changing world. The aim of the aforementioned research (Foster, 2020) was to engage with a sample of Northumbria University students to explore how, why and with what purpose they interacted and engaged with a learner analytics platform in order to develop a theory of user adoption. Critical Realism was combined with Grounded Theory (see Oliver, 2012; Blunt, 2018; Hoddy, 2018) and offered a methodological space to explore and develop a theory. That theory aimed to be simultaneously generalisable whilst acknowledging through CR that the profiles would never wholly define an individual student experience. Critical realist grounded theory was a useful vehicle for navigating students' understanding of their own experiences and their adoption of an analytics platform however I often wrestled with the Realist ontology as I did not begin with a problem nor did I search for a solution. Rather I set out to explore, as with the present research, the opportunities afforded by analytics within a wider strategy which had both operational and theoretical elements.

The literature review conducted for this thesis highlights that student mental health and the identification and evaluation of intervention strategies are both complex and circumstantial. In deciding to underpin the current research with a relativist ontology I was influenced by Cruickshank's *A Tale of Two Ontologies: an immanent critique of Critical Realism* (2004). This work highlighted for me the importance of ontological questions and that I may in some way honour my appreciation of the ambitions of Critical Realism by utilising an ontology which best matches the context of the present research and, specifically how the resulting knowledge may be applied in a real setting. Furthermore, Bilgrami (2002) suggests that realism and relativism are not opposing doctrines. By confronting the tensions between them, namely around the extent to which beliefs are wholly or only partially false and the struggle between knowledge status over knowledge value, I may provide results from this study which are both practically useful and theoretically valuable. This commitment to one ontology across both qualitative and quantitative methods reflects my commitment to transparency in the present research; I argue that philosophical neutrality is impossible in an approach as exploratory in nature as the present one where many assumptions are made alongside proxies designed in the data for conditions in reality. aligned to my reading of Hathcoat and Meixner (2017), which is discussed in the next section on Pragmatism.

To summarise there are two considerations which are important to the ontological choice to underpin this current research with Relativism (Baghramian and Carter, 2021), a theory which holds that a phenomenon *may* occur when the conditions of independent social variables and paradigms are met.

Firstly, when approaching the task of profiling students based on their mental health data combined with other factors, it must be accepted from the outset that students will almost certainly belong to multiple profiles. Their data footprint across the platforms investigated in this study, although informed by known risk factors, will likely suggest traits which conflict with our existing understanding of student mental health and are constrained by real world events such as system outages or loss of service for which data-driven approaches may struggle to account.

Secondly and simultaneously to the first consideration, university support teams are arbitrary constructs comprising of people with specifically defined skill sets rather than common values or socio-political views; the ethical sensitivities around data driven and algorithmic profiling therefore reduces the likelihood of identifying a single and generalisable rule which defines their collective adoption or rejection of a process such as SMHP. These are important considerations when underpinning the present research with Relativism rather than Realism as the latter accounts for objective, and singular truth existing outside of the human experience; "Scientific realism is the view that theories refer to real features of the world. 'Reality' here refers to whatever it is in the universe (i.e., forces, structures, and so on) that causes the phenomena we perceive with our senses" (Schwandt, 1997, 133). Scientific Realism therefore does not leave the current research open to the possibility that SMHP may be valid and valuable in some circumstances but not others nor what the conditions for its success may be in a university setting and the extent to which the human actors may influence its adoption. Without such understanding this thesis would focus more on the validity of the profiles and less on their utility in a real university environment thus failing to achieve its aim of understanding the opportunities it may afford. Instead, when considering the current research it follows that a relativist ontological stance will allow for the multiplicity of 'truths' (Crotty, 1998; Collis and Hussey, 2003) inherent in the success or failure of student mental health analytics as an accepted and operationalizable approach to improving student wellbeing support. The use of data and analytics to understand the needs and behaviours of the entire student population provides real benefits and economies of scale for university service designers even though, by its very nature, it rarely results in a depiction of 'the actual experience of every or any individual wholly' (Foster, 2020). I argue this doesn't limit the research but frees it of the onus to be scientifically exact and thus operationally unachievable; it renders it pragmatic.

3.2.2. Pragmatism

My academic publication record to date reflects the early stage at which I find myself in my 'second career' as a researcher; I have worked professionally within the realm of data and technology for over 15 years and am an experienced analyst and specialist in student data and university administration. Much of my professional career has been spent seeking best practice and designing, delivering and evaluating projects from an academically informed foundation due to my close collaboration with senior academic colleagues who commissioned much of the institutional research. The view that research should provide "utility" rather than simply to represent the most accurate account of reality (Rorty, 1999xxvi) is important in terms of the need to take action on the student data which we collect and analyse if the ultimate goal is to influence and improve outcomes. My approach to the exploration of analytics in HE has therefore evolved alongside an epistemological appreciation of Pragmatism (Peirce, 1992 and 1999; Dewey, 1999) and more specifically the work of Rorty (1999) as a means to reconcile my identities as an academically inclined professional and a professionally occupied academic.

> "Our depreciatory attitude toward "practice" would be modified if we habitually thought of it in its most liberal sense, and if we surrendered our customary dualism between two separate kinds of value, one intrinsically higher and one inherently lower" (Dewey, 1929)

Pragmatism is often discussed in relation to anti-dualism which bemoans the separation of the metaphysical realm (where idea and knowledge exists) from action and doing however critics suggest that this neglects to appreciate the historical importance of the two realms as a heuristic device (Carson and Rowlands, 2001). I can appreciate this criticism in as much as such devices can give structure, order and scaffolding for researchers. However pragmatism offers, to me and to the current research at least, a bidirectional bridge whereby its tolerance for practice based methods allows me to feel comfortable in the pursuit of actionable and impactful research on Student Mental Health Analytics. Pragmatism's openness for abductive, deductive and inductive approaches at relevant points in the sensemaking process facilitates a grounded and useful understanding of both the conceptual and real context, in which a change in MHW support, can occur. That is, in a growing sector with rising levels of student mental health issues, there must be efficient, evidence-based inquiry which leads to timely and impactful actions with measurable outcomes. 'For there is a relation between the value of an increased certainty of an item of knowledge and the cost of such increase of certainty, which enables us to determine whether it is better to expend our genius, energy, time, and money upon one investigation or upon another.' (Peirce, 1974, para 85.). With so many approaches to improving student mental health available (the full list of bids which were submitted in the current competition was over 50), the pragmatic approach is to produce something which has both academic and practical utility.

3.2.3. Mixed Methods

Scientific approaches to population structuring have evolved from demographic analysis (as pioneered by Graunt and Malthus) to classifications based on social and political ideals such as wealth, health, skill and class. These 'discourses', Foucault argues, are methods of creating knowledge and power (Foucault, 1969) and have facilitated the rise of interpretative paradigms which, I argue, are at the centre of modern segmentation analyses concerned with influencing human behaviour and health. As a piece of research underpinned by ontological Relativism and epistemological Pragmatism, it is my hope that the theoretical findings of this thesis are actively considered by universities and used to improve mental health service provision; this will consequentially have practical implications which impact real students who need support. Therefore, in the present research, the grouping of students based on their mental health data to inform improved services can only be achieved by embracing the strengths of both quantitative and qualitative enquiry; how may we group students and how we may use these groupings require two different yet complementary data approaches.

Generally, it is upheld by the mixed methods research community that the use of both quantitative and qualitative approaches within the same study are practical and may indeed complement each other (Maxcy, 2003; Creswell et al., 2003). To reconcile them with a pragmatist or rather neo-pragmatist approach however requires the researcher to be apparent of the moral and political consequences of the inquiry (Denzin, 2012) and the ability to navigate a complex philosophical landscape fraught with incompatibilities (Hathcoat and Meixner, 2017); this has been the case in the current research with the transparency regarding its ontological and epistemological undeprinnings. When considering mixed methods research underpinned by a pragmatic epistemology one must look in the mirror and ask whether the maxim 'choose the combination or mixture of methods and procedures that works best for answering your research questions' (Johnson and Onwuegbuzie, 2004, 17) invites too much naivety into the research design. Conversely, it may represent the freedom to find one's methodological soulmate which is completely tailored to the current research context.

Recognising that there is a lack of understanding around student mental health profiling in the extant literature and currently no student mental health profiles exist, quantitative methods will be used to create some and used as stimuli for discussion. Qualitative techniques will be used to analyse data from interviews with university support staff where profiles are presented and discussed. As such a mixed methodology has been adopted to assess the validity and scope for SMHP as a method of segmenting the student population to better target and personalise mental health support.

The aims and objectives have been structured such that RQ1 naturally aligns to the quantitative data results and RQ2 the qualitative, however the critical discussion on both must incorporate both the quantitative and qualitative aspects of the research; this ensures that the mixed methods approach exists not only as a data collection approach but one which aims "to obtain different but complementary data on the same topic" (Morse, 1991, 122) i.e. to create student mental health profiles from quantitative data and validate the accuracy and relevance of the profiles from a stakeholder perspective. The remainder of this methodology section will discuss the aspects of mixed methods research design which have been considered and incorporated into this thesis.

In qualitative terms grouping like individuals, theoretically or otherwise, may be termed 'typologies' (Doty and Glick, 1994) however quantitative practice prefers the term clustering. Cluster analysis is the grouping together of subjects within a dataset that display similar characteristics or patterns of behaviour; clusters display a healthy level of visual convergence on statistical charts. Indeed being able to see subjects clustered together is one of many methodologies for accepting the validity of cluster analysis. An alternative to quantitative clustering would have been to sample the population and perform interviews and focus groups to determine Student Mental Health Profiles however there are several challenges to this including the need to engage with students on all aspects of the mental health spectrum. Given there are yet no known student mental health profiles this inductive approach, presented ethical risks and challenges which could be mitigated by first considering the data objectively. Therefore, due to the size of the datasets being utilised in this study, and to adequately set a foundation for more qualitative inquiry in future, a quantitative methodology is proposed for the generation of Student Mental Health profiles which will allow for meaningful and robust analysis that can be replicated, investigated and challenged in future settings. There is the risk that quantitative methods may be perceived as wholly positivist by subjecting mental health outcomes to crude data exploration so that the profiles I identify have little relevance or context for researchers and practitioners alike. This risk is mitigated by the second phase of the research where practitioners were invited to scrutinise the approach and the outputs of the quantitative phase.

> 'The combination of multiple methodological practices, empirical materials, perspectives, and observers in a single study is best understood as a strategy that adds rigor, breadth complexity, richness, and depth to any inquiry' (Denzin, 2012,82)

Denzin's argument for the application of triangulation as a means to validation has gone through several iterations and first began as an approach to using multiple qualitative methods rather than incorporating quantitative analyses alongside. Denzin appears to have become philosophically affected by the 'use, abuse and misinterpretation' of the single term triangulation; 'Can we retake the discourse surrounding this word and retrofit it to a postmodern world where meanings and politics are refracted off of the edges of crystals, not triangles?' (Denzin, 2012, 85). I interpret his desire to reclaim the term for a more complex modern world as an argument for its applicability to this study which sits at the intersection between so many jarring political narratives including the use of data profiling to support individuals within a larger population, and the juxtaposition of targeted and personalised mental health services with privacy, surveillance and limited resources.

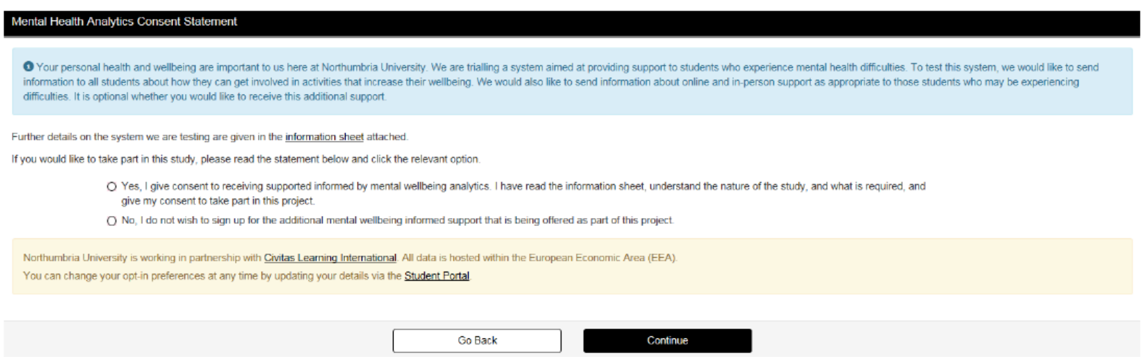
3.3. Research Design

3.3.1. Research terminology

For the purpose of this study, 'clusters' refer to the output of a statistical modelling process where an algorithm groups students based on correlations and patterns. On their own clusters have no meaning as it is not always apparent why students have been grouped together. 'Profiles' are the interpretation of the clusters using descriptive data about students to understand the characteristics of the grouped students. 'Targeting' is the action whereby University Support Services proactively promote interventions or support to students based on their profile. 'Personalisation' is the strategic alignment of an intervention to a profile based on additional knowledge such as efficacy and relevance; whilst this thesis does not seek to understand which profiles may better engage with certain personalised interventions it does seek to understand whether the approach facilitates a better understanding how interventions may be personalised.

3.3.2. Data collection activities

Data collection took place over a period of 13 months. Students were asked if they would like to participate in the research at enrolment via an invitation embedded in the enrolment process in September 2020. A screenshot of the consent text is shown in Figure 2 below and the WHO-5 data collection in Figure 3.



Mental Health Analytics Consent Statement

Your personal health and wellbeing are important to us here at Northumbria University. We are trialling a system aimed at providing support to students who experience mental health difficulties. To test this system, we would like to send information to all students about how they can get involved in activities that increase their wellbeing. We would also like to send information about online and in-person support as appropriate to those students who may be experiencing difficulties. It is optional whether you would like to receive this additional support.

Further details on the system we are testing are given in the information sheet attached.

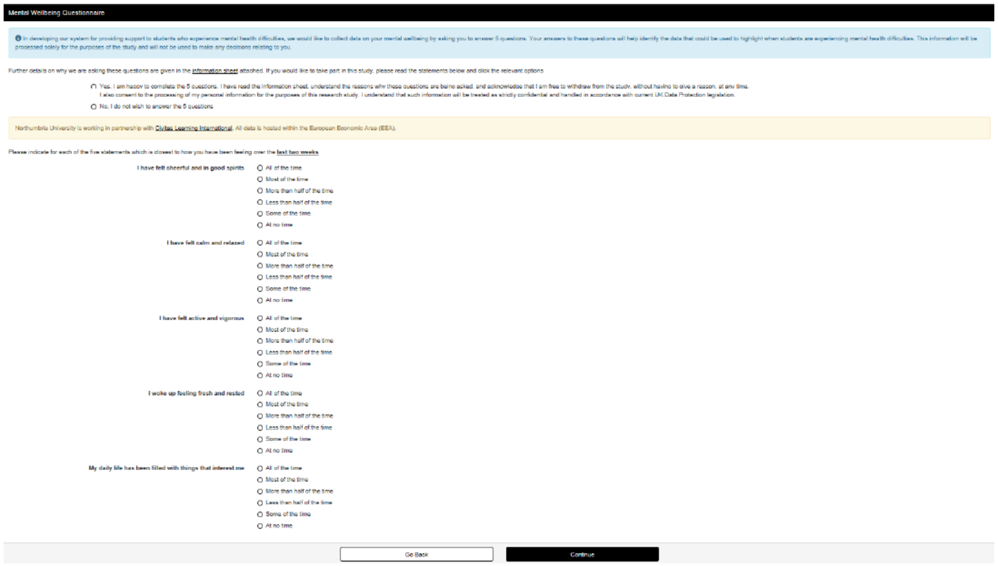
If you would like to take part in this study, please read the statement below and click the relevant option.

- Yes, I give consent to receiving supported informed by mental wellbeing analytics. I have read the information sheet, understand the nature of the study, and what is required, and give my consent to take part in this project.
- No, I do not wish to sign up for the additional mental wellbeing informed support that is being offered as part of this project.

Northumbria University is working in partnership with Civitas Learning International. All data is hosted within the European Economic Area (EEA).
You can change your opt-in preferences at any time by updating your details via the Student Portal

Go Back | Continue

Figure 2 Mental Health Analytics Opt-In Screen in the mandatory Enrolment Task


Mental Wellbeing Questionnaire

In developing our system for providing support to students who experience mental health difficulties, we would like to collect data on your mental wellbeing by asking you to answer 5 questions. Your answers to these questions will help identify the data that could be used to highlight when students are experiencing mental health difficulties. This information will be processed solely for the purposes of the study and will not be used to make any decisions relating to you.

Further details on why we are asking these questions are given in the information sheet attached. If you would like to take part in this study, please read the statements below and click the relevant options

- Yes, I am happy to complete the 5 questions. I have read the information sheet, understand the reasons why these questions are being asked, and acknowledge that I am free to withdraw from the study, without having to give a reason, at any time. I also consent to the processing of my personal information for the purposes of this research study. I understand that such information will be treated as strictly confidential and handled in accordance with current UK Data Protection legislation.
- No, I do not wish to answer the 5 questions

Northumbria University is working in partnership with Civitas Learning International. All data is hosted within the European Economic Area (EEA).

Please indicate for each of the five statements which is closest to how you have been feeling over the last two weeks

I have felt cheerful and in good spirits
- All of the time
- Most of the time
- More than half of the time
- Less than half of the time
- Some of the time
- At no time

I have felt calm and relaxed
- All of the time
- Most of the time
- More than half of the time
- Less than half of the time
- Some of the time
- At no time

I have felt active and vigorous
- All of the time
- Most of the time
- More than half of the time
- Less than half of the time
- Some of the time
- At no time

I woke up feeling fresh and rested
- All of the time
- Most of the time
- More than half of the time
- Less than half of the time
- Some of the time
- At no time

My daily life has been filled with things that interest me
- All of the time
- Most of the time
- More than half of the time
- Less than half of the time
- Some of the time
- At no time

Go Back | Continue

Figure 3 WHO-5 data collection screen in the enrolment task, September, 2020

The whole student population were asked again in March and in May via email surveys sent by the operational project lead. As much of the literature was point in time and some actively avoided addressing the issue of seasonality, these time points were chosen to accentuate fluctuations at the key points in the student journey such as enrolment and assessment so as to get a realistic picture of student mental health. Over the summer of 2021, data was then collected from source systems (Student Records System, Customer Relationship Management system "CRM" and Virtual Learning Environment "VLE") via Microsoft SQL server query to create a master data set combining mental health data and supplementary student information for example age, gender and grades (linked to the known risk factors identified in the literature review). Finally, six interviews with stakeholders were conducted in October 2021 which concluded the data collection.

3.3.2.1. WHO-5 Data and Collection in 2020/1 Academic Year

As it underpins so much of the student mental health profile creation, which is a major part of this research, it is essential to give an overview of the WHO-5 metric. The WHO-5, or "World Health Organisation 5", is a subjective measure of wellbeing; it asks the respondent to elaborate on the frequency with which they have experienced five scenarios over the last 14 days . The questions and grading are shown in Table 2.

Table 2 WHO-5 Questionnaire

Over the last two weeks:	*All the time*	*Most of the time*	*More than half of the time*	*Less than half of the time*	*Some of the time*	*At no time*
1. I have felt cheerful and in good spirits	5	4	3	2	1	0
2. I have felt calm and relaxed	5	4	3	2	1	0
3. I have felt active and vigorous	5	4	3	2	1	0
4. I woke up feeling fresh and rested	5	4	3	2	1	0
5. My daily life has been filled with things that interest me	5	4	3	2	1	0

The combined WHO-5 score is derived by summing the individual components of the questionnaire and multiplying by 4 e.g. if a respondent answered that they had experienced each scenario only some of the time in the last two weeks this would means a score of 20 (5 questions multiplied by a score of 1 multiplied by a scale of 4 = 20). It is a globally utilised measure of wellbeing and has been found to be a valid screening tool for depression, translating well to fields of study outside of clinical medicine (Topp et al., 2015). An assumption which this study makes is that the WHO-5 is an appropriate metric for clustering a full spectrum of mental health profiles not just at the lower end of the scoring scale indicating depression (a score less than 13 from a maximum of 25) but also those students reporting higher scores and therefore more positive feelings of wellbeing. Whilst the aggregated WHO-5 score is typically used to clinically categorise and diagnose respondents, this study also considers the individual scores e.g. “I have felt cheerful and in good spirits” to understand whether WHO-5 component scores can inform profiles and thus facilitate better targeting of students rather than just one combined score.

The WHO-5 data points are similar to a 6-point Likert scale, as such the data used for clustering is ordinal; an assumption in this thesis therefore is that the distance of sentiment between each available response is equal.

At present there are already existing methods of grouping respondents of the WHO-5 survey using their score without the use of clustering (Krieger et al, 2014; Topp, 2015); the validity of these 'cut-offs' however has only recently been investigated in terms of their reliability (Sischka et al, 2020). Specifically, Sischka et al. (2020) measured the standard errors for frequently used WHO-5 score groups (28 and 50) and found that differentiating respondents at these clinical 'cut-offs' was reliable but poses issues when comparing scores internationally.

The Hamilton Depression Rating Scale ("HAM- D") (Hamilton,1960) is an observer rated measure for depressive symptoms. This differs from the WHO-5 scale which is self-reported. Krieger et al. (2014) investigated the relationship between the HAM-D and the WHO-5 score and found there to be a strong relationship between the two although *extreme* depression is not as easily identified using the WHO-5 as it is with the HAM-D(see Figure 4).

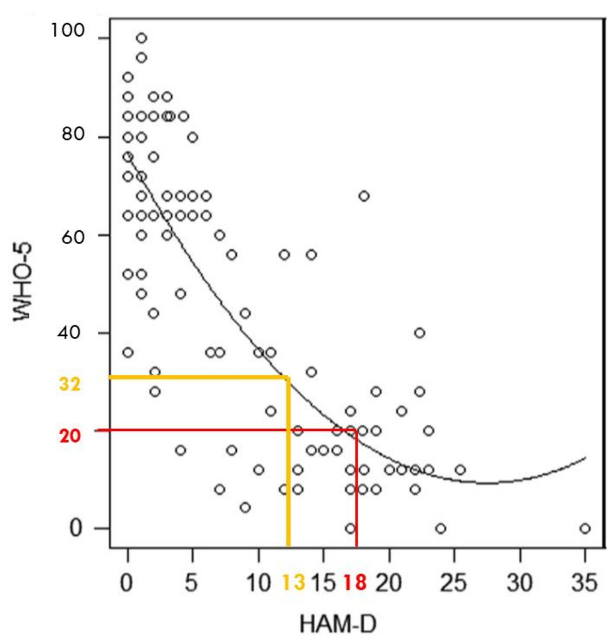


Figure 4 adapted from Krieger (2014) to show correlation between Hamilton Depression scale and WHO-5 scoring

Krieger et al. assert that:-

- an HAM-D score of 18 (major depression) corresponded to a WHO-5 score of 20
- an HAM-D score of 13 (minor depression) corresponded to a WHO-5 score of 32

In addition to the Hamilton Depression label it is also widely considered that a score of less than <50 indicates poor wellbeing (Topp,2015). This cutoff was validated as part of Sischka's et al (2020).

Given that there are multiple cutoff points available to researchers but that, as yet, the extent to which they improve criterion validity remains inconclusive (Sischka et al., 2020) the present research considered multiple cutoff points as part of its exploratory nature. As such the pre-profile descriptive analysis utilises the following groupings:-

- Major Depression where the WHO-5 score was less than 20
- Minor Depression where the WHO-5 score was less than 32
- "Low Wellbeing" where the WHO-5 score was less than 50
- OK Wellbeing where the WHO-5 score was more than 50
- Bespoke student groupings where the WHO-5 score cutoff shows statistically significant trends

Furthermore, from a longitudinal perspective and as per the WHO-5 documentation produced by the WHO Collaborating Centre for Mental Health, Frederiksborg General Hospital, when analysing data which considers the *change* in wellbeing over multiple time points, a percentage score should be derived. According to Ware, 'A 10% difference indicates a significant change' (Ware, 1995) and therefore this guidance has been applied in this study.

The WHO-5 data were collected via three independent surveys which represent key points in the student journey; September captures wellbeing sentiment at enrolment, March captures wellbeing data just after the first Semester has concluded including Semester 1 assessments and May represents the end of the study year and post Semester 2 assessment period. This is in direct response to failings in the literature

(Sam and Eide, 1991) to confront stressor points and ensure that the data is reflective of the fluctuations expected around certain times in the calendar.

Students studying at one of Northumbria's European campuses in Newcastle, London and Amsterdam were eligible for the survey along with distance learning students (this therefore excluded offshore franchised and validated provision). The first was via an invitation embedded in the enrolment process in September 2020. It asked them to read the project information sheet and students who agreed to participate and share their data with the project were asked to complete the WHO-5 survey. The following two survey invitations were sent out in March 2021 and May 2021; as students were already enrolled it was not possible to collect it via the same method as the first time therefore the survey link, which was designed using Microsoft Forms, was sent out via email to students' university email accounts. This change in survey methodology impacted the rate of response as it is not guaranteed that students would read their university email whereas the enrolment task was a mandatory action and therefore was seen by all. 18,698 responded to the first survey which is 93% of the total eligible population; this compares to 3,741 (19%) for the March survey and 3,486 (17%) for the May survey. The rationale for the enrolment survey being embedded in the enrolment task was a project decision to maximise engagement with the project and gather as much data as possible to build a predictive mental health model which is part of a separate workstream within the wider OfS project. Whilst it would have been desirable to have collected the scores using a consistent methodology throughout the year the number of participants is high enough across each of the 3 collection points to remain a valid sample of the total population and as such I argue this does not invalidate the clusters or profiles identified.

3.3.2.2. Supplementary Data to Support Descriptive Analysis and Profiling

After each stage of the WHO-5 data collection, SQL Server was used to query university databases to extract student level data based on the risk factors identified in the literature. The Northumbria University databases queried were the Student

Record System, data warehouse and commercial products including the Virtual Learning Environment (Blackboard) and the Customer Relationship Management system (Microsoft Dynamics). This supplementary data collection was highlighted in the WHO-5 survey participant information sheet so that only the datasets outlined in the ethics sheet were accessed and only extracted for the students who consented to participate.

As the data collected would be used to create profiles which aimed to capture a wide range of aspects about the student experience, a balance was struck between demographic, circumstantial and behavioural data and were informed by the literature review. A key principle of this element of data collection was that it should focus on existing datasets available at the university. As such no new data was collected which meant there were some notable omissions from the literature review which were not included.

One of the key risk factors which was omitted was data on whether a student had previously had a mental health concern, engaged with any mental health services (university or external) and the satisfaction of experience with those services if applicable. These were highlighted as important factors for disclosure (though not necessarily of experience) but were not included in the supplementary data harvest This decision was a project one based on a regard for students privacy and the distress this may cause from an ethical perspective. Furthermore, creating a proxy for this from our internal records was deemed to be intrusive; this extended to satisfaction of service as to have answered a survey would indicated engagement; furthermore current tools for measuring satisfaction within the team were inconsistent and not available for the time period under study. Instead the only proxy linked to self-declared wellbeing was the welfare queries raised in the CRM however these do not necessarily indicate an episode of poor mental health. CRM data were also used to gave an understanding of what students were raising enquiries about and if they were asking for support with factors known to impact student mental health including debt and finances (Cooke et al, 2004).

Research suggests that age, gender and nationality have an impact on both the university experience and students' mental health (Andrews and Wilding, 2004) therefore these data were included in the clustering process where available. A relationship was also found between the impact of stress and depression on academic performance (Hysenbegasi, Hass and Rowland, 2005) therefore data on previous assessment results was included.

The work of Tinto (1997) suggests that the feeling of being part of a community is important to the student experience and research also exists which links differential student experiences with additional responsibilities such as childcare and pregnancy (Manze, Watnick and Freudenberg, 2021) and the demands of employment (Yorke and Longden, 2008). As such two questions were created as proxies for these factors as part of the existing student support practice at Northumbria University. These questions were: "Do you feel part of the Northumbria community" (Yes / No) and "Do you have any additional responsibilities such as caring, work or childcare" (Yes / No); the questions were not mandatory to answer and students opting in to the study were made aware that these questions would be included.

To capture academic engagement, the VLE was used as a reliable digital engagement metric; as the research was conducted during Covid-19 restrictions it was not possible to consider physical on campus engagement such as attendance at class or visits to the library. VLE data also meant that this metric was appropriate for distance learning students where no physical engagement is expected. The following VLE behavioural variables were derived for each student at the March and May census points:-

- the total count of login events to the VLE
- the average count per modules attempted of login events to the VLE
- the total hours spent on the VLE
- the average hours per modules attempted spent on the VLE

It is important to note that not all data sets are available at all points in the academic year. For instance it is not possible to create a profile based on VLE engagement for new students in September as they have not yet commenced their study. As such data were used only where available and relevant to the specific point that the WHO-5 survey was released. The final variables included in the clustering and profiling process are outlined in Appendix 2: Appendix 2a: Supplementary data availability at each census point.

The CRM data was split by the following types for added granularity:-

- Welfare enquiries
- Mitigation (requests for extensions to assignments or Personal Extenuating Circumstances claims which are where unforeseen events mean the student cannot engage fully with their studies resulting in an assignment deferral)
- Finance enquiries
- Change of Circumstances enquiries (requests to change course, take a break in study or withdraw from university study)
- General enquiries

The supplementary data was added to the WHO-5 data collected via the surveys to create a primary dataset; this was used as the input file for the exploratory cluster analysis which led to the creation of student mental health profiles (see *3.3.3.2 Exploratory Clustering to Create Student Mental Health Profiles*).

3.3.2.3. Meta data collected during clustering

Exploratory clustering (Kassambara, 2017) requires ongoing investigation and evaluation of several established clustering approaches such as hierarchical (Ward, 1963) and partitional clustering; therefore it was important to use statistical tests to create meta data about the clusters to inform analysis decisions. There were two key data points collected during the clustering process; the Hopkins Statistic[8] and the optimal number of clusters[9].

3.3.2.4. Semi-structured interviews via Microsoft Teams

The data collection concludes by gathering qualitative data from research participants via semi structured interviews; Adams' applicability checklist outlined in the *Handbook of Practical Programme Evaluation* (1994) was useful in confirming that this approach had several merits. See Appendix 2 for a mapping of the current research to this checklist showing it meets three of the four possible scenarios outlined by Adams; it should be noted that the list was not inferred to be exhaustive.

It was important to ensure that the participants were fully informed about the research before participating in the interviews; this meant asking for their consent but also there needed to be transparency about the research methodology and the aims and objectives. As such, prior to the interviews, participants were asked to watch a 20-minute video outlining an anonymised worked example from the enrolment data through the clustering analysis and then the profiling process. This was an opportunity to clearly define the terms clustering and profiling as well as what the intended use of these profiles was i.e. targeted and personalised interventions. This was followed up by a presentation to all participants via Microsoft Teams which presented the whole suite of profiles at each point in the academic year. This was required as it was the only opportunity to go through the entire suite of profiles which had been created using the quantitative data; it was considered to provide this by email however there existed a

[8] The Hopkins statistic is used before clustering happens to ascertain the cluster tendency of a dataset (Hopkins and Skellam, 1954). This statistic is available via the factoextra R package and the output is on a scale of 0 to 1 where 0 indicates data that is already arranged in well defined clusters and 1 indicates that the data is random. This statistic is useful to understand whether there is a need to even cluster the data at all or whether the raw data can be used for profiling.

[9] Clustering indices from the NbClust R package (Charrad et al, 2014) were used to determine the optimal amount of clusters for each dataset based on the 'majority rule'. For partitional clustering i.e. K Means clustering, it is essential to specify the amount of clusters required therefore this package was used extensively to explore optimal cluster amounts for each cluster method and dataset. It was also used for the hierarchical clustering to 'cut' the data into clusters for analysis. The data outputs of the NbClust package also include graphical visualisations of the D-Index, Hubert, Silhouette, Elbow and Gap statistics- each of which provide insight into the amount of student clusters which should be considered.

risk that the profiles could have been misunderstood or taken out of context which would have impacted the quality of the follow up interviews. The presentation offered a chance for questions to be asked which benefited the whole group. Finally 30-40 minute interviews were conducted via Microsoft Teams as soon after the Live presentation as possible; the first commenced directly after the live presentation and the last was conducted 6 days after. The presentation was recorded so that it could be watched again by participants before the interviews and an on-screen refresher of the profiles was offered during the interview. Whilst face to face interviews would have been preferred due to the benefits of social interaction and researcher/ participant engagement (Opendakker, 2006), Covid-19 restrictions meant this was not advisable and ethically it was felt that this put participants at too much risk of infection as this would have required public transport, being on campus and being in an enclosed space. That said, the remote means were as effective in terms of picking up on social queues and certainly facilitated easy visual engagement by means of zooming in on certain features on a shared screen and highlighting areas of importance. An added advantage of the electronic means of interview was the automated transcription software and in-built recording options offered by Microsoft Teams.

Eligible participants were identified based on their role within Northumbria University's CMH team. This excluded staff working in generic student support services (e.g. frontline staff handling calls and supporting with general course enquiries); it also excludes those roles which manage specific welfare and safeguarding incidents. The main criteria for inclusion in the research was that they were working within the student mental health and counselling team and were formally trained to deliver mental health support which therefore excluded administrators who are responsible for managing appointments, and one coordinator who coordinates the administration of the service and supports management with systems, processes and publicity.

In total 16 participants were invited to interview via an email to those who met the above criteria. Seven chose to participate in the research activities however unfortunately the seventh was unable to engage. This nonprobability approach to sampling is purposive but essential given the necessity of restricting the scope of discussion to that which is relevant to the present research (Eskes et al., 2016). Specifically, whilst this approach excludes a vast array of opinions on student mental health profiling (most notably from students themselves but also other roles within the team and out in faculty) this is noted here a necessary limitation justified by the need to concentrate on the business unit primarily aimed at serving students' mental health support needs.

Two participants are categorised as 'service leaders' having a hybrid delivery role; they serve students both at an individual level but also with strategic responsibility for delivering a student MHW service. Four participants have the role of 'Practitioner' although there are various types of role within this designation (Mental Health, Counsellor or Psychological Wellbeing Practitioner). Due to the low sample size these are not disclosed at the individual quotation/ data level to preserve anonymity. The range of roles and responsibilities included in the research participant group is essential to capture a whole service appraisal of student mental health analytics as an approach as well as ensuring that they could draw on experiences with students from across the mental health spectrum (i.e. those from very poor mental health with scores of 0/100 to thriving students with scores of 100/100).

The interview followed a semi-structured approach and therefore each interviewee had the chance to elaborate and reflect on areas of specific importance to them; the researcher also had the opportunity to delve deeper into themes as they arose and follow relevant and unexpected ideas. See Appendix 2 for the list of questions asked and rationale for each.

3.3.3. Data Analysis

In the context of the current research the descriptive analysis of WHO-5 data begins very broadly and is designed to navigate a large data set in search of insights which relate to what is known or noted as missing from the literature on student mental health profiling. This happens first followed then by further exploratory clustering (given there is little in the current research to inform the basics of a clustering method for such a data set); subsequently the research then moves to profiling and finally the qualitative data collection and analysis occurs in order to triangulate the approach with members of the counselling and mental health team. This sequential mixed methods approach is most appropriate for research designs which (Creswell et al., 2003). Another valid option would have been to undertake concurrent analysis whereby the profiles were created, shared and worked upon over a period of several iterations. The benefit of the latter would be potentially more usable profiles which would encourage greater buy-in from practitioners due to the cocreational nature of the research. The disbenefit would be the time constraints on the project; given this thesis acts as a first step towards further iterations, this decision does not impede future research in this area.

3.3.3.1. Exploratory data analysis to understand the student population

The explanatory-sequential approach (Creswell et al., 2003; Ivankova, Creswell and Stick, 2006) is a mixed methods research design which uses a quantitative foundation and then uses qualitative data to augment the results and add further interpretative dimensions (this is usually denoted as QUAN then QUAL). Superficially, the current research design would seem to conform to this analysis approach; however, as the qualitative interviews are designed to explore rather than explain the profiles, I argue that the present research also draws on Edmonds and Kennedy's (2017) method called the exploratory – sequential approach whereby quantitative data is used exploratively to augment qualitative findings. For Edmonds and Kennedy this qualitative step occurs first i.e. QUAL then QUAN, from which the present research differs.

The proxies used to contextualise the mental health data are informed by the literature review which itself is essentially a qualitative step in the research process however it would be a stretch to suggest that the current research design conforms to Edmonds and Kennedy's approach because I begin from a quantitative baseline aligned to RQ1. However, where the dataset is adequately large, I argue that quantitative data can be used for exploratory purposes at the beginning of a QUAN then QUAL research process providing the research questions are open to discovery [10] and where hypothesis testing may limit findings in a new area of research.

Given the purpose of the current study is to explore, rather than explain, the opportunities for student mental health profiling I have chosen to adapt the two previously discussed methods rather than formulate or test a hypothesis. The research embraces a process of emergence whereby each step of data collection or analysis contributes to the next. A depiction of this process compared to two use cases is presented overleaf to illustrate the similarities and differences and outline, specifically the analysis details for each step.

In summary, I begin by using statistical significance testing and other descriptive data techniques on the WHO-5 and supplementary student data to discover which of the proxies identified are most pragmatic for clustering and profiling. For this I will use known mental health groupings identified in the literature as well as bespoke groupings where the data suggests that the current research population may not conform to the findings of previous studies- where this is the case I have highlighted these in the results section.

When taking an emergent research approach to research, the decisions taken at each step must be logged and transparent as I wish to still persevere a strong element of reproducibility. Given the exploratory nature of the research, there was a need to only present the relevant results from the initial descriptive data section: relevance was determined based on two factors: the literature review (a prior themes) and the findings of from the qualitative data collection process (new themes identified).

[10] see Ivankova, Creswell and Stick, 2006, where they discuss the alignment of a quantitative research question to the first step of their explanatory- sequential study

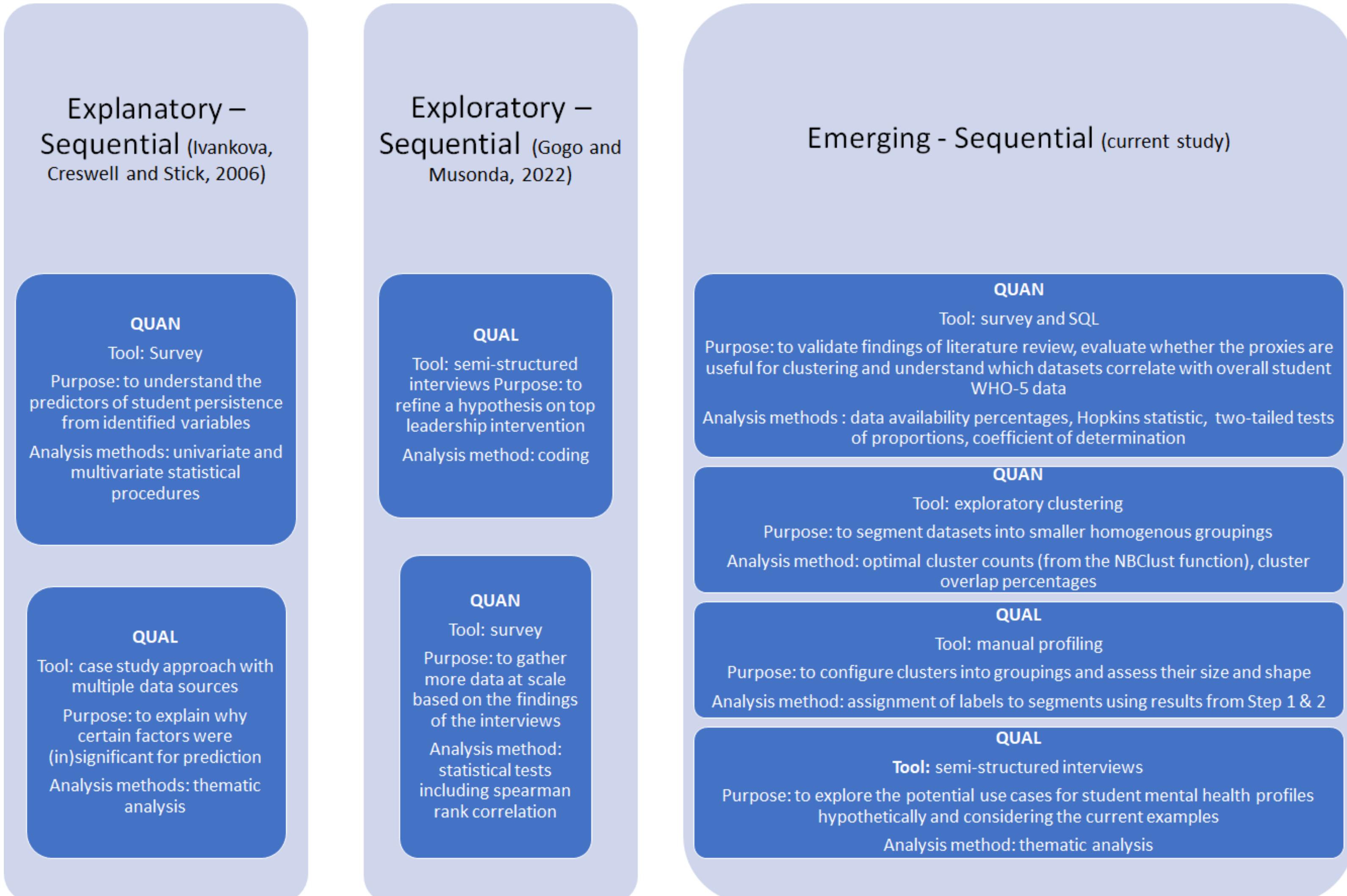


Figure 5 Emerging - Sequential Approach compared to other sequential methods

3.3.3.2. Exploratory Clustering to Create Student Mental Health Profiles

A two-stage exploratory clustering approach (Starks et al, 2010) was applied to the WHO-5 and supplementary data; this is more appropriate than a fixed clustering approach as there is very little in terms of previous research which would suggest how to approach the clustering of student WHO-5 data. There are two types of clustering, hierarchical and partitional. When considering hierarchical clustering there are two further subcategories: Agglomerative ('bottom up') and divisive ('top down'). Hierarchical clustering facilitates the visualisation of clusters in the popular dendrogram format whereas partitional does not. However partitional clustering is highly applicable in scenarios where the dataset is large as is the case with some of the datasets in this study. Oftentimes researchers in fields which utilise clustering heavily such as cell biology and botany will set out with a specific clustering approach in mind to ensure that their results and findings are consistent with previous studies however there is very little precedent in the case of clustering student mental health that would influence that decision. Exploratory clustering means experimenting with different clustering approaches to better understand the impact that each approach can have on the clusters and consequentially the student mental health profiles generated. In this sense it can be described as a 'traditional' method of processing and classifying behavioural data (Canhoto and Backhouse, 2008) as the profiles are not automatically generated from the clusters. This study used exploratory analysis to present multiple approaches to clustering thus facilitating more open discussions during the interview phases.

During the data preparation phase in Microsoft Excel a small amount of analysis was conducted such as visual checks on the data and basic descriptive statistics to verify validity before loading the dataset into the R Studio programme. The remainder of analysis involved performing the clustering, preparing data visualisations and summarising outputs in tabular format for the results chapter; these steps were undertaken via scripted analysis code in R Studio. There are many advantages of using

R Studio compared to other analysis suites such as SPSS and Minitab. Although knowledge of coding is required which may be a drawback for some researchers, it is open source and has a vibrant community which makes it easy to access free support. Open source means that in the future scripts can be read, adapted and used without fear of licensing issues or incompatibility. Scripting and documenting the analysis trail precisely facilitates reproducibility which aids the verification of claims to new knowledge (Gandrud, 2020). R Studio has a wealth of clustering packages available, along with written documentation and community support. Whilst this helped with the exploratory nature of the clustering approach , it did also lead to an overwhelming level of choice which meant that a great deal of time was spent evaluating each package to ensure that it was aligned to the research design and computationally viable (in terms of both volume of data and the types i.e. ordinal and non-numerical). See Appendix 2: for a detailed list of how and why certain packages were taken and how they were deployed.

Once the clustering process was completed, data tables were created; rows summarised the WHO-5 Score and columns aligned to the cluster. Profile generation was not automatic; it took a lot of time to analyse the overlaps to identify common factors influencing the clustering which was not immediately apparent in all cases. Whilst clustering is a scientific process, profiling in this research manifested as a more inductive approach where patterns needed to be searched for and uncovered.

Profiles were labelled literally and without attempt to assume student circumstance or sentiment (noted as a risk by Kreuter et al., 2003); this is important as the profiles are generated using only quantitative data rather than qualitative insight which would help to contextualise the social or emotional characteristics of the profile. There are examples in quantitative clustering studies where labels are used to aid the understandability of a profile even though the risk of adding a value judgement is acknowledged (Seghers and Rutten, 2010); the introduction to Ketchen and Shook's article in Strategic Management Journal (1996) provides a useful summary of some of the criticisms that have identified in the use of clustering and the potential for it "to offer inaccurate depictions of the groupings in a sample but also to impose groupings where none exist" (Ketchen and Shook, 1996, 442). Certainly there must be acknowledged a difference between profiling and stereotyping where 'the conclusions [of the latter] are not supported by inductive logic' (Boylan, 2011). I agree that labelling poses risks which have the potential to skew the qualitative data collection process and, in turn, the knowledge contribution of the present research. Literal labelling allowed participants to infer their own meaning and make a personal interpretation between the profile and a potential intervention or impact on their practice which is most appropriate in a mixed methods design where the presentation of the profiles to participants is integral to the findings of the research. As an example, profiles based on academic performance were described relative to the grade itself, "Students averaging at most a third class" rather than an interpretation of what a good grade is e.g. "Academically underachieving students".

3.3.3.3. Validating profiling as an approach to targeted and personalised student mental health and wellbeing support

The final step in the analysis section was to review interview transcripts which were automatically generated by the Microsoft Teams programme. Recordings were shared with participants via email afterwards so that they could review their answers; this is considered by many qualitative researchers to increase trustworthiness (Poland, 1995). No participant chose to make any revisions or clarification; only two replied (and suggested the interview was a true reflection of their thoughts and feelings on this topic). Low response rate is consistent with one of the disadvantages of an approach which seeks to engage with research participants in this way (Mero-Jaffe, 2011).

Nevertheless, it is argued that this does not invalidate the data given the extent the researcher took to review the transcripts for linguistic accuracy which was necessary as, with most transcription software, the accuracy of the software was low and a variety of regional dialects compounded this issue. As such the researcher listened back to the videos and updated the transcript to ensure that they reflected the true words of the researcher and interviewee. This step is important for both data accuracy but also for data absorption whereby it facilitates an opportunity to reflect, at a very low and detailed level, on the meaning of each sentence and phrase. This data absorption was further enhanced by listening to the audio repeatedly in daily life such as in the car, on the train and at different times of the day to become familiar with the similarities and the differences between participants.

Recognizing the pragmatic epistemology of the study and discrete purpose of this qualitative element (i.e. to seek the views of staff engaged in student mental health and wellbeing service design and delivery), a simple thematic data analysis approach was adopted to facilitate commentary on whether the SMHP approach, regardless of technical viability, was considered useful in practice, in what cases and under what conditions.

Collis and Hussey (2003) suggest that once transcription is verified for accuracy, analysing qualitative data presents several challenges, namely reducing the data, structuring the data, anticipating data reduction and detextualising data. The work concludes that "the synthesis and reorganisation of data should lead to the development of themes and patterns which can be confronted by existing theories or used to construct new theories" (Collis and Hussey, 2003, 279). In support of this statement, Yin (2003) explains that the aim of data analysis is to treat the evidence fairly, produce compelling analytical conclusions and rule out alternative interpretations. The benefit of thematic analysis is its flexibility (Vaismoradi et al., 2013) however, at times too much flexibility can introduce spurious concepts and analysis, with data not linking directly back to the original research aims.

As such the analysis commenced with an iterative process of explanation building developed by Yin (2003) which involved reviewing narrative from the semi structured interviews to identify key themes. Strauss and Corbin (1998) and King (2004) note such analysis typically starts with the creation of priori codes which identify themes strongly expected to be relevant to the study. Priori themes were created based on the OFS (Office for Students) project criteria which shaped this study;

- the validity of the data used and the profiles generated
- the appropriateness of the methodological approach taken to create the profiles
- the opportunities and risks associated with a strategy for using data and profiles to target and personalise support

Once the priori codes were created an initial review of interview transcripts commenced with manual annotation. From this early analysis process, a range of additional themes emerged as important. These new themes allowed for further additions and revisions to the template. Such a continuous process of re-reading the interview transcripts was repeated 2-3 times a week over a period of eight weeks to ensure the researcher was immersed in the data. Reviewing individual accounts on a number of occasions also enabled a manual approach to thematic analysis with emerging themes based on the initial priori codes recorded on a spreadsheet. This reflects the views of Perry (1999) who considers manual forms of analysis are more than adequate when a researcher is so immersed in the data.

Many themes emerged, often similar in nature, for example discussions relating to clinical tools other than the WHO-5 (e.g. the GAD-7 and PHQ-9) and the resources available to take a proactive approach. Reviewing individual accounts on several occasions proved particularly valuable as it enabled similar themes to be grouped and a better understanding of the context in which stories were shaped to emerge (King, 2004). Similarly, the original research question and objectives were also regularly revisited to ensure themes which were not of direct relevance could be disregarded. Ultimately this approach allowed for not only identifying the themes across the whole data collected but also honing in on the relationships between questions one and two (roles, responsibilities and data utilisation and literacy) and questions three to five (thoughts on the profiles identified and the opportunities for student mental health) to facilitate a discussion on profiling in a real university setting where roles and structures play an important part in the adoption, maintenance and success of interventions.

Finlay (2002) highlights the importance of researcher reflexivity when undertaking qualitative data analysis but also the difficulty in engaging with it in practice. This requires reflection on the nature of the researcher's involvement in the research process, and the way this shapes its outcomes to confront and therefore consciously navigate around any bias. As a previous colleague of the participants within the wider student engagement and wellbeing directorate and institutional advocate for analytics practices, I openly hold views and assumptions about the phenomenon under investigation. As such, consideration about how such views and assumptions could influence the way data was interpreted was important and so I adopted a reflexive stance in the data analysis process. This involved the creation of a mini biography (see Appendix 2) and a research journal (see Appendix 2 for a photograph of entries from around the time of data collection). The biography, written in the first person for added resonance, enabled me to reflect upon my professional and academic experiences to date to better understand how this could influence data interpretation; this included my previous roles as a planning analyst, performance manager and Senior manager responsible for Student Services. This was read ahead of any transcription review but, due to its personal nature, wasn't shared with anyone. The research journal further provided an opportunity to better understand how data was captured and interpreted. This was a hand-written record of thoughts and feelings from both the data collection process and the subsequent creation of themes; it provided an opportunity to ensure my experience was not influencing the interpretations but also a useful reminder of the actions taken to document in my methodology e.g. regarding transcription software.

3.4. **Key lessons learned for future research**

There are a number of outcomes from the present research which may offer guidance to a researcher undertaking a similar research study in future. An overarching lesson is that the data collection method should, as much as possible, be incorporated into a formal method of data capture which students can engage with regularly to avoid lags between census points. This will ensure that descriptive analysis of a longitudinal nature can better isolate points where population level wellbeing changes rather than specifying points in the academic cycle.

Secondly, in focussing the context of mental health to a particular setting (in this case a University setting) it is difficult to incorporate a broad range of evidence from the wider body of public health knowledge. This was evident for example when reviewing the risk factors of mental health where it was necessary to focus on factors specifically relating to the student experience but consciously omitting key factors in the literature review and subsequent methodology including trauma, previous experience of mental health disorder, personality data and data on psychological determinants of disclosure such as resilience. This does not invalidate the present study however it does mean that future studies may wish to use the existing public health research as a baseline from which the student experience can be measured by using an appropriate, hypothesis driven research design to quantify the differences between the populations. Whilst an exploratory analysis plan has facilitated flexibility around WHO-5 cutoff points and data types (e.g. continual or ordinal) it did mean that a lot of analysis was conducted and, in the end, omitted due to it being irrelevant or spurious. As such it is not appropriate for a study with limited resources on researcher time or cost.

Finally, for future research which looks specifically at the impact of profiles on service design and delivery, I would suggest that it is not necessary to create bespoke profiles in advance of the qualitative data collection exercise. Whilst this was useful in the present study to facilitate a discussion on how they were created and why, this did lead to discussions which were more focussed on the technicalities of the profiles rather than the philosophy or theory of using them. There are other ways to mitigate this such as including research participants, whether staff or student, in the design of the profiles themselves or, as with the present study, host a pre-data collection session which focuses on methodology and operates as an informal question and answer session. This may be better done on an individual basis as the questions that participants ask may inadvertently influence other participants' understanding of the profiles or their validity.

4. Results

This chapter is presented in five sections with the final section summarising the two areas of results; 4.1 is a descriptive analysis of the WHO-5 and risk factor data. 4.2 details the clustering process and 4.3 details the translation of clusters into profiles providing commentary on whether data improves population segmentation. These results act as evidence to understand how student mental health profiles can be created using WHO-5 data and data on known risk factors (RQ1).

Section 4.4, presents qualitative data on how and with what purpose staff engage with student data currently and how they consider targeted and personalised student mental health support for all students. Their thoughts on the opportunities and risks of profiling for proactive support offer the evidence to assess how university support staff may use profiles to deliver a Whole University approach to student mental health (RQ2).

4.1. Descriptive Analysis of WHO-5 data and potential risk factors

4.1.1. Demographic information

81.1% of students completed the survey when it was included in the mandatory enrolment task compared to a significantly lower population in March and May (Table 3).

Table 3 Number of respondents to each WHO-5 survey

	Sep-20	Mar-21	May-21	Total Responses
n	18,598	3,741	3,486	25,825
First time respondents	18,598	1,120	750	20,468
Respondents to a previous survey	n/a	2,621	2,736	
Percentage of eligible population	81.1% (18598/22936)	11.5% (3741/32595)	10.3% (3741/33722)	
Average age *Respondents (eligible)*	24.8 (24.8)	24.4 (24.9)	24.9 (24.9)	
Gender split	55% Female, 45% Male, 0% Other Gender	61% Female, 38% Male, 0% Other Gender	57% Female, 42% Male, 0% Other Gender	

In total there were 25,825 responses made up of 20,468 unique students. The average age of respondents at each survey point was between 24.4 and 24.9 years old, which, compared to the eligible population between 24.8 and 24.9, suggests the samples are representative of that demographic characteristic. The gender split is also static between 54-55% females to 45-46% males depending on the census point therefore the enrolment survey dataset is most representative of the gender split with females being slightly overrepresented in the March and May surveys.

4.1.2. Analysis of WHO-5 data

The high-level results for each WHO-5 survey are included here in Table 4.

Table 4 Summary of WHO-5 Results by Census

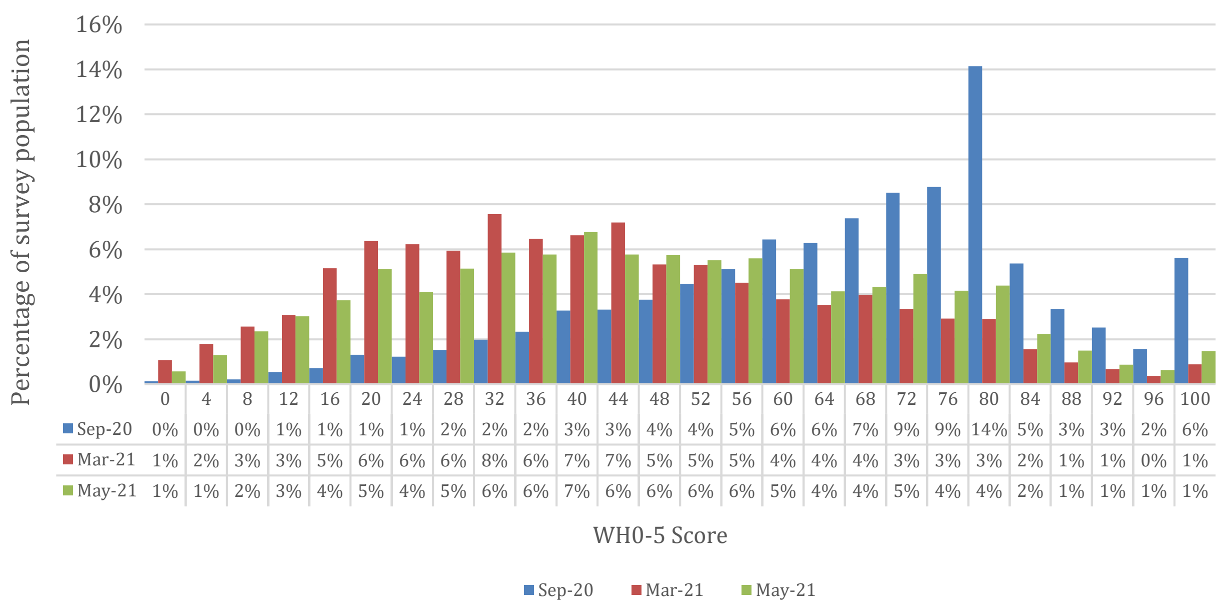
WHO-5 Score	September N, %, Cum.	March N, %, Cum.	May N, %, Cum.
0	24, 0.1%, 0.1%	40, 1.1%, 1.1%	20, 0.6%, 0.6%
4	30, 0.2%, 0.3%	67, 1.8%, 2.9%	45, 1.3%, 1.9%
8	40, 0.2%, 0.5%	96, 2.6%, 5.4%	82, 2.4%, 4.2%
12	100, 0.5%, 1%	115, 3.1%, 8.5%	105, 3%, 7.2%
16	132, 0.7%, 1.8%	193, 5.2%, 13.7%	130, 3.7%, 11%
20	243, 1.3%, 3.1%	238, 6.4%, 20%	178, 5.1%, 16.1%
24	228, 1.2%, 4.3%	233, 6.2%, 26.2%	143, 4.1%, 20.2%
28	283, 1.5%, 5.8%	222, 5.9%, 32.2%	179, 5.1%, 25.3%
32	368, 2%, 7.8%	283, 7.6%, 39.7%	204, 5.9%, 31.2%
36	434, 2.3%, 10.1%	242, 6.5%, 46.2%	201, 5.8%, 36.9%
40	609, 3.3%, 13.4%	248, 6.6%, 52.8%	236, 6.8%, 43.7%
44	618, 3.3%, 16.7%	269, 7.2%, 60%	201, 5.8%, 49.5%
48	700, 3.8%, 20.5%	199, 5.3%, 65.4%	200, 5.7%, 55.2%
52	830, 4.5%, 24.9%	198, 5.3%, 70.6%	192, 5.5%, 60.7%
56	950, 5.1%, 30.1%	169, 4.5%, 75.2%	195, 5.6%, 66.3%
60	1198, 6.4%, 36.5%	141, 3.8%, 78.9%	178, 5.1%, 71.4%
64	1169, 6.3%, 42.8%	132, 3.5%, 82.5%	144, 4.1%, 75.5%
68	1371, 7.4%, 50.2%	148, 4%, 86.4%	151, 4.3%, 79.9%
72	1585, 8.5%, 58.7%	125, 3.3%, 89.8%	171, 4.9%, 84.8%
76	1632, 8.8%, 67.4%	109, 2.9%, 92.7%	145, 4.2%, 88.9%
80	2631, 14.1%, 81.6%	108, 2.9%, 95.6%	153, 4.4%, 93.3%
84	998, 5.4%, 87%	58, 1.6%, 97.1%	78, 2.2%, 95.6%
88	623, 3.3%, 90.3%	36, 1%, 98.1%	52, 1.5%, 97%
92	469, 2.5%, 92.8%	25, 0.7%, 98.7%	30, 0.9%, 97.9%
96	290, 1.6%, 94.4%	14, 0.4%, 99.1%	22, 0.6%, 98.5%
100	1043, 5.6%, 100%	33, 0.9%, 100%	51, 1.5%, 100%
Total	**18598**	**3741**	**3486**

4.1.2.1. Seasonality

On average student mental health was significantly higher in September (66.3) and lowest in March (42.4). Although the average score improved to 47.5 in May it still remained significantly lower than September. See Appendix Table 2 to 6 for a full overview of the results across the three surveys. Only 3.1% of students would be grouped as having Major Depression using the WHO-5 to Hamilton D translation (see

3.3.2.1) in September compared to 20% and 16.1% in March and May respectively (see Appendix Table 3). These patterns can be observed in Figure 5 which shows the distribution of WHO-5 scores for each survey population and highlights a large spike for scores between 60 and 84 at September.

Two-tailed tests of proportions were carried out (df = 1) to understand where there were significant differences between the population distribution by aggregated score for the first and second survey and the second and third survey (see Appendix Table 6 for resulting p values- and chi-squared statistics). The null hypothesis is that there is no statistical difference between the population level distributions of student mental health scores at different points in the academic year. We can reject this hypothesis as the data shows there are clear and significant differences with students being significantly less likely to score 48 or less ($p < 0.001$) and significantly more likely to score 60 or above ($p < 0.001$) in September.



	0	4	8	12	16	20	24	28	32	36	40	44	48	52	56	60	64	68	72	76	80	84	88	92	96	100
Sep-20	0%	0%	0%	1%	1%	1%	1%	2%	2%	2%	3%	3%	4%	4%	5%	6%	6%	7%	9%	9%	14%	5%	3%	3%	2%	6%
Mar-21	1%	2%	3%	3%	5%	6%	6%	6%	8%	6%	7%	7%	5%	5%	5%	4%	4%	4%	3%	3%	3%	2%	1%	1%	0%	1%
May-21	1%	1%	2%	3%	4%	5%	4%	5%	6%	6%	7%	6%	6%	6%	6%	5%	4%	4%	5%	4%	4%	2%	1%	1%	1%	1%

Figure 6 Percentage of the survey population by WHO-5 score

Considering only the students who answered both surveys (n = 2,621), 72.2% of students had a significant wellbeing decline (more than 10% as per Ware, 1995) between September and March. 1,216 students responded to both the March and May surveys; 33.9% (n = 412) of students had a wellbeing decline greater than 10% which is not as stark a trend as was witnessed between September and March due to March results being the lowest for the academic year; 41.5% students improved their wellbeing during these points. Figures 6 and 7 (overleaf) present these changes graphically.

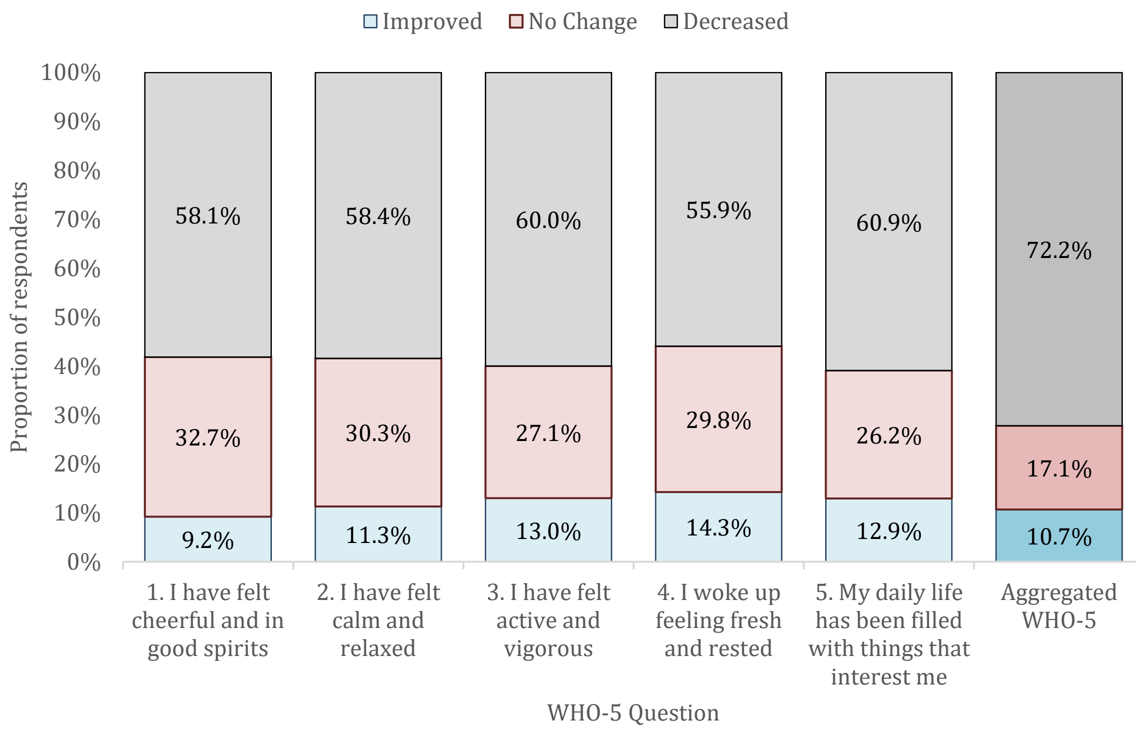


Figure 7 Change in wellbeing scores between September and March by question at the student level

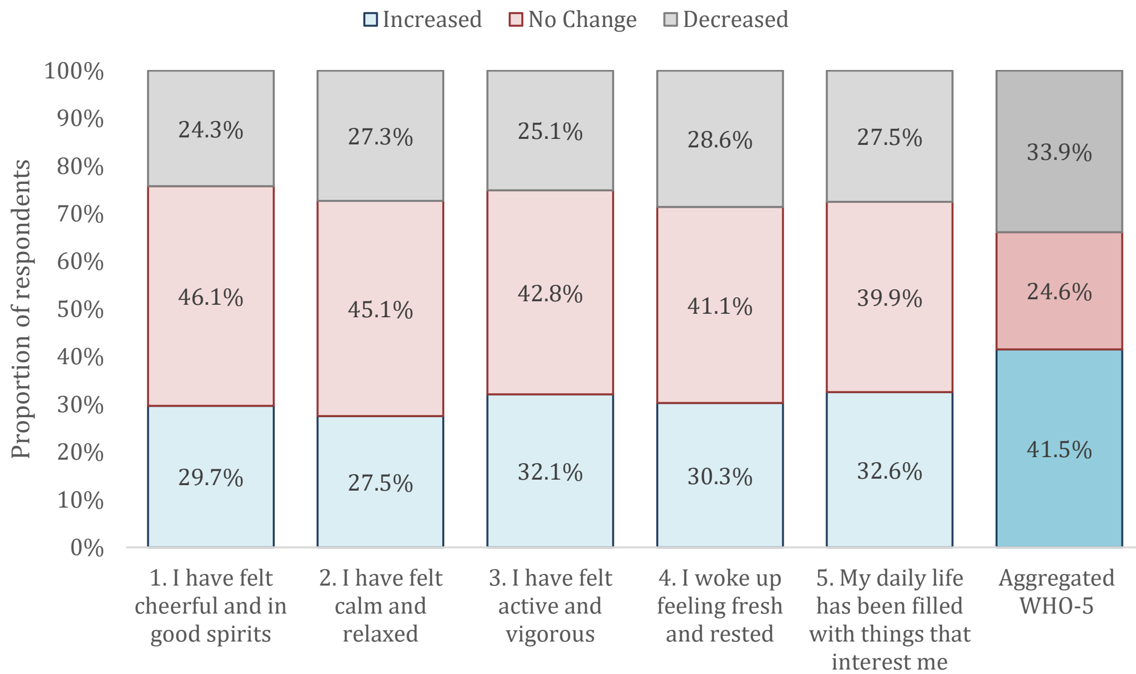


Figure 8 Change in WHO-5 scores between March and May: Student Level

899 students answered all three surveys throughout the year; 28.0% (n = 252) had a wellbeing score over 50 at all three checkpoints however Appendix Table 4 shows that the majority of students (63.2%, n = 568) experienced significant fluctuation (more than 10%) in their wellbeing at least once in the academic year.

4.1.2.2. Question level analysis

Appendix Table 7 to 9 show survey responses by question and answer for each census point; the most frequently given answer is “most of the time” to all five questions in September however this changes in March and May as students start to report lower scores. In September, only 0.5% of students said that in the previous two weeks they had not felt cheerful or in good spirits at all which is significantly lower ($p < 0.001$ in all cases) than the remaining four questions; this is nearly nine times lower than the rate at which students declared they had not, in two weeks, woke up feeling fresh and rested suggesting the cheerfulness facet will be useful for narrowing down to a target population on an area known to have the strongest correlation with overall WHO-5 score.

Question 1, “I have felt cheerful and in good spirits” has the highest average score in each survey. Appendix Table 10 contains the standard deviation by question for each survey; Q1 also has the lowest variance of the questions for September and March. Conversely, question 4, “I woke up feeling fresh and rested” has the highest variance and the lowest scores in all three surveys. Of the other 4 questions, Q4 has the lowest correlation with Q1 in all three surveys as shown in Appendix Table 11; this table also shows the intercorrelation between each WHO-5 question ranges from 0.58 (Q2 and Q5 in March) to 0.75 (Q1 and Q2 in September and May).

4.1.3. Analysis of data on student mental health risk factors

4.1.3.1. Demographic data (gender, age and fee status)

Appendix Table 12 to 15 shows the WHO-5 groupings by demographic data, including the data for the population of students for whom no data was available[11].

The average WHO-5 score for female students was 63.3 compared to 70.1 for male students and 43.1 for students of other genders. The sample size for students who defined their gender as ‘Other’ is incredibly small and should be treated with caution with respect to statistical significance testing; nonetheless the results suggest that this group of students are more likely ($p < 0.05$) to have a WHO-5 score which indicates either major or minor depression (a score of 32 or less).

There is no correlational relationship between WHO-5 and age ($R^2 = 0.23$) however there are peaks and troughs in the data which warrant further exploration including an observable trough on the chart for students aged 20,21 and 22 (highlighted in bold in Figure 9 below). 21 year olds exhibit the lowest wellbeing scores across the population (average = 62.1) and significantly lower scores than other students in their 20s; 9.8% of 21 year olds had a score less than 32 versus 8.3% for

[11] When collecting supplementary data there is a small percentage of students in each dataset where individual data was not available in the source system. This could be for a variety of reasons including the enrolment status of the student at the census point and data capture/ systems failure. They are presented here for descriptive purposes but were not used in the clustering process.

others in their twenties, ($p < 0.01$). Furthermore whilst age, as a continual variable, may not show a significant correlative relationship, mature students over the age of 50 were far more likely to record a score of more than 50/100 compared to their younger peers (85.8% versus 79.5%, $p < 0.001$).

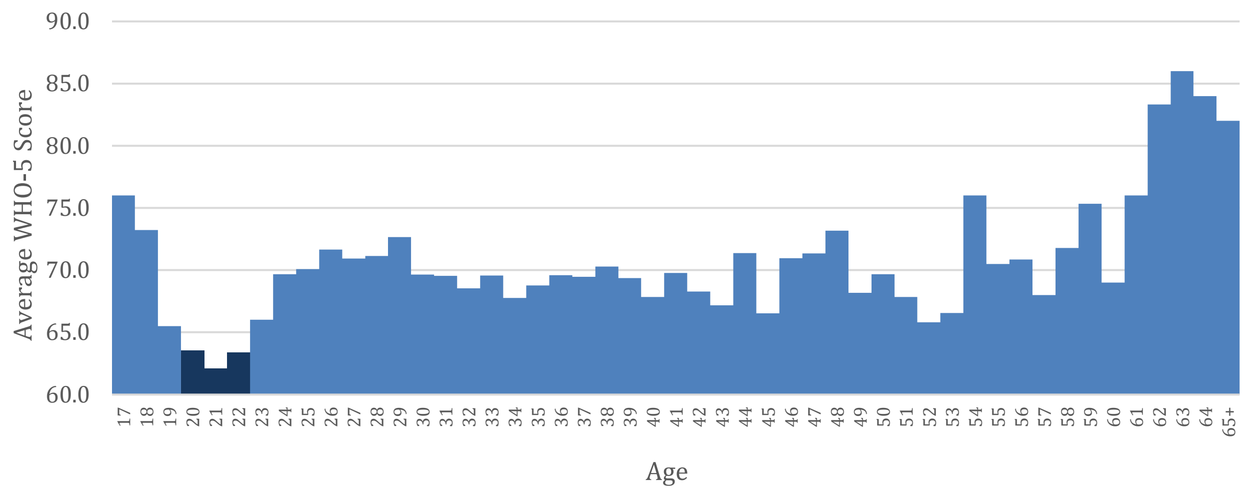


Figure 9 September 2022 Average WHO-5 score by age

International students were significantly more likely to report positive wellbeing (90.2% scoring over 50 versus 76.9% for home students, $p < 0.001$). Figure 10 shows WHO-5 distribution by Fee status which highlights this trend.

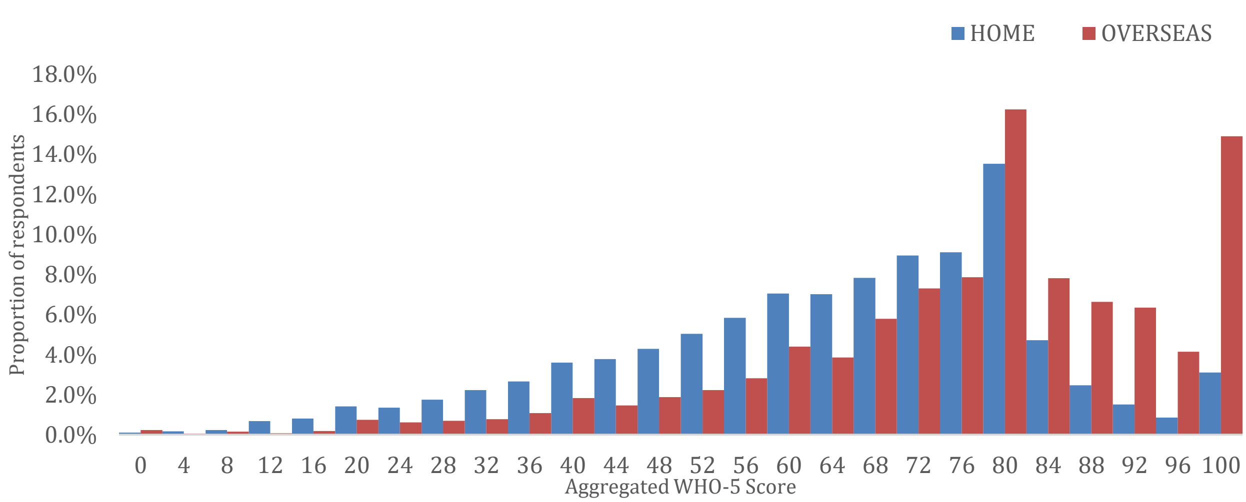


Figure 10 Aggregated WHO-5 Score by Fee Status

4.1.3.2. Community and additional responsibilities data

Appendix Table 16 and 17 show the results for the questions related to feeling part of the community and having additional responsibilities.

Tests of proportions shows that there are no statistical differences between the wellbeing scores of students with additional responsibilities ("Do you have any additional responsibilities such as caring, work or childcare "-- Yes / No) compared to those without. Considering the proportion of students reporting low scores indicating major or minor depression (a score of 32 or less) the difference was 0.1% which is not significant ($p = 0.38$). Furthermore, considering the proportion of students scoring above 50 (which would indicate ok to positive wellbeing according to the literature), the difference between those with additional responsibilities and those without is 0.8% which again is not significant ($p = 0.15$).

However, considering "Do you feel part of the Northumbria community" (Yes / No), the results show that there are significant differences in aggregated WHO-5 scores for students who report that they do feel part of the university community compared to those who don't. 84.0% of students who feel part of the community scored their wellbeing above 50 across the five questions compared to only 62.4% of those who did not feel part of the university community which is significant ($p < 0.001$). Figure 13 shows the distribution of the population by community sentiment.

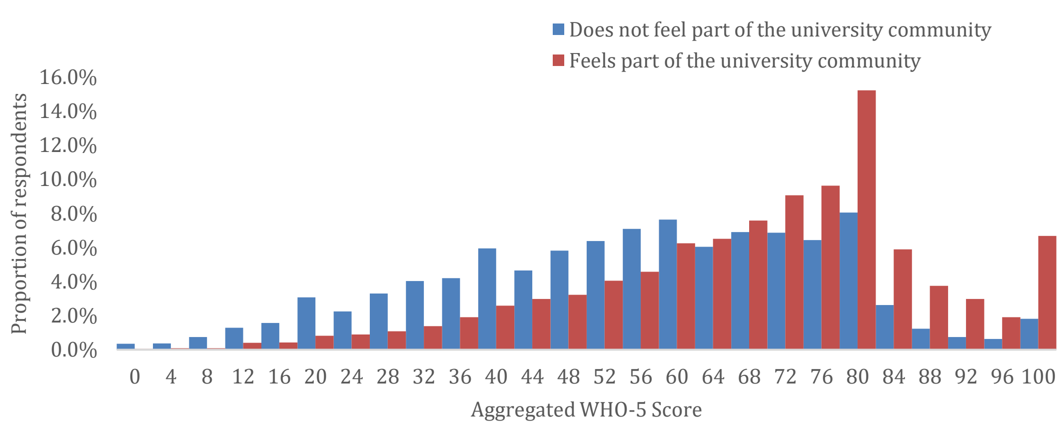


Figure 11 Aggregated WHO-5 Score by community sentiment

4.1.3.3. Engagement with the Virtual Learning Environment

Appendix Table 18 to 26 contain the aggregated WHO-5 scores grouped by VLE engagement. In summary, of the 3741 students who answered the WHO-5 questionnaire in March, 2565 (68.6%) had logged in to the VLE at least once; of those users, the average time spent online was 85.2 hours with an average of 52.7 logins per module. Figure 12 is a visual representation of the VLE variables for March plotted against the aggregated WHO-5 data.

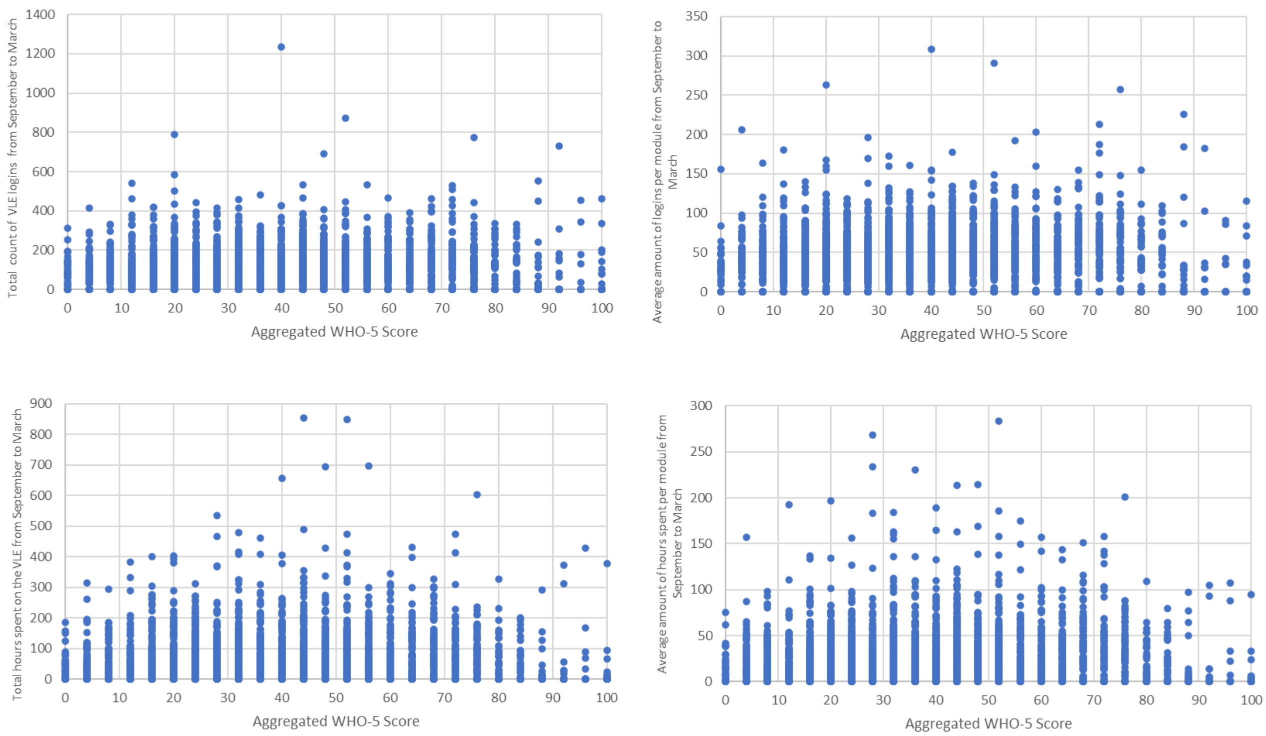


Figure 12 Scatter plots for each VLE variable versus the aggregated WHO-5 score

No trends are observable in the scatter plots suggesting the correlative relationship between VLE engagement and the WHO-5 data is very low. A comparative set of scatter charts are available for the May dataset in which evidence a similar result. This is further confirmed by the calculation of correlation coefficients for each variable (see Appendix Table 22).

There are however some notable changes in behaviour between March and May which warrant exploration. In March 31.4% (n = 1176 / 3741) of students did not log in to the VLE at all during Semester 1; of these 28.5% (n = 335 / 1176) were suffering from poor wellbeing (a score < 32). In May only 2.1% (n = 73 / 3486) of students had not logged in during Semester 2 which is significantly lower ($p < 0.001$); of the 73 students who did not log in 28.8% (n = 21) were suffering from poor wellbeing (a score < 32) which is a similar rate to March.

4.1.3.4. Engagement with the Support Services via CRM

Of the 3741 students who answered the WHO-5 questionnaire in March, 539 (14.4%) had used the CRM to seek support at least once; see Appendix Table 27 for a breakdown by WHO-5 Score and

Appendix Table 28 for a detailed breakdown by ticket type. In March, students who sought any type of support via CRM during semester 1 were significantly less likely to report WHO-5 scores over 50 compared to those who didn't use CRM to raise a support ticket (27.8% versus 35.8%, $p < 0.001$).

Appendix Table 28 includes data for tickets labelled Change of Circumstances "ChoC"; this is the process a student initiates if they wish to withdraw from their course, take a leave of absence or transfer to a different programme. In total there were 277 students who raised a ChoC ticket between September and March, this includes 232 students who only raised a ChoC plus 45 students who raised other types of tickets too. 29.6% of students (n = 82/277) who raised a choc reported very low wellbeing scores (<22) compared to only 19.3% of students who did not initiate a ChoC which is a significant difference (p < 0.001). This trend was observable for scores up to 72 as can be seen in Figure 13 where the p value remains at 0.00 signalling significantly lower wellbeing scores. These tests do not consider causality and therefore it cannot be stated, using statistical tests alone, that seeking a ChoC impacts or is impacted by wellbeing however this theme is explored later in the chapter via the qualitative interviews.

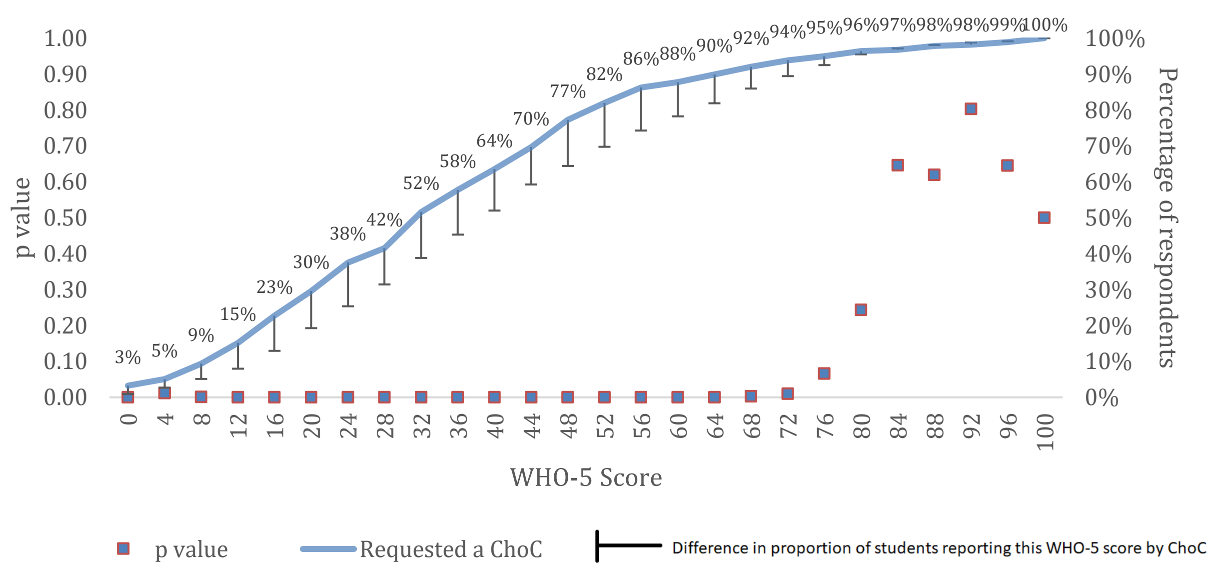


Figure 13 Significance in the difference of WHO-5 Scores between students requesting a choc and those who did not

Considering other types of support, 8 students sought support for a welfare issue; of those who raised multiple types of tickets there were a further 9 students who sought help for a welfare issue. 30.4% (n = 17 / 56) of students who sought help reported very low wellbeing scores (less than 22) compared to only 18.9% (n = 606 / 3685) of those who did not seek help for any issue. This suggests some meaningful statistical difference ($p < 0.05$) however not as strong as is observed for Change of Circumstances.

Given the high levels of fluctuation in wellbeing across the year it is pertinent to revisit CRM data on support seeking to ascertain if these behaviours changed significantly between March and May (see Appendix Table 29 and 30). In March 85.6% of respondents (n = 3,202 / 3,741) had not sought any support via the CRM which compares to 67.2% (n = 2,341 / 3,486) in May. Students seeking multiple types of support have the highest proportional levels of very low wellbeing (a score of less than 22) whereas it is statistically more likely (p=0.00) that students who do not seek support via the CRM report positive wellbeing (51.9% with a score over 50 compared to 30.2% of students who sought some sort of support). As observed in March, students who have engaged with the ChoC process in May report significantly poorer wellbeing; 24.6% of students who requested a ChoC (exclusively or alongside other support) had a WHO-5 score indicative of major depression compared to only 15.4% of students who did not. This is comparative to the March results.

4.1.3.5. Previous Academic performance

At the September census point previous academic performance is only available for students continuing their study at the university and is not available for new students. Appendix Table 31 to 35 outline the results discussed in this section. The results by grade show that continuing students who averaged a grade less than 50 were more likely to be in the category of major depression (a score less than 33 on the WHO-5) than those continuing with a higher grade (5.8% versus 3.6%, 3.2% and 3.8%, p < 0.01 in all cases).

The results by count of failed modules show that 37.7% of students with three or more failed modules reported a score less than 50 compared to 24.8% of those with

2 or less; therefore students who failed 3 or more modules in the previous academic year were statistically more likely ($p<0.001$) to have low wellbeing. The R squared value for count of failed modules is 0.005 and for grade is 0.002; these low values suggest that in isolation the variables do not explain much of the variance in the WHO-5 scores. As an example this scatterplot of grades by WHO-5 score evidence the week relationship.

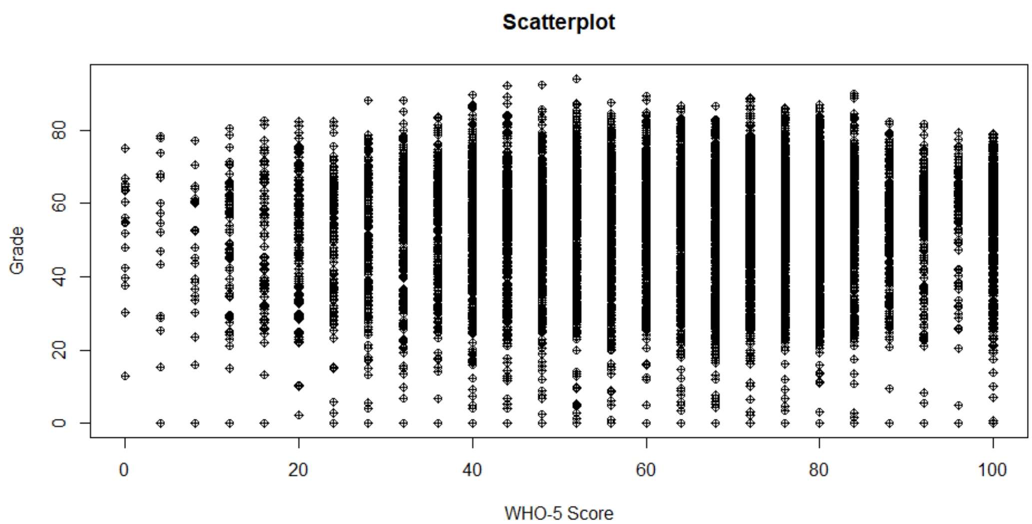


Figure 14 Scatterplot of previous academic grades in September by WHO-5

By May, the majority of students have been assessed and therefore the volume and availability of previous academic data has increased since September. Although the sample sizes are too small to analyse at the count of failure level, aggregating up to "Failed a module" (n = 102) shows that 40.2% of students who failed reported wellbeing scores lower than 22 compared to only 15.3% of students who didn't fail which is significant ($p < 0.001$). As per the results from the previous analysis of academic data, grades have a low correlation with WHO-5 score ($R^2 = 0.02$).

4.2. Clustering to make WHO-5 Student Mental Health profiles

4.2.1. Clustering with WHO-5 data

The initial dataset to undergo clustering was the WHO-5 data captured during September enrolment; due to the computational demand required to cluster all 18,598 observations, a random sample of data was taken (n = 3,500, 18.8%) by using the 'sample' function in the R package 'dplyr'. The Hopkins statistic, a test of cluster tendency, is 0.54 for the September WHO-5 sample dataset; this suggests that there is very little cluster nuance available across the five questions which would support meaningful cluster segmentation. The NBClust function was applied to the sample data; the optimal number of clusters calculated is 2 for both hierarchical and partitional approaches (see Appendix Figure 3 Histograms showing optimal cluster amounts using NBClust for WHO-5 data only); this confirms that using WHO-5 data alone yields little segmentation. Using the 'factoextra' package to create the dendrogram and cluster chart (Appendix Figure 4), it is clear that one cluster is considerably bigger than the other in the agglomerative approach (left). In both approaches there was a cluster with higher wellbeing and a cluster with lower wellbeing however, crucially, there are overlaps on the mid wellbeing spectrum where analytics has differentiated students on more than just the aggregated WHO-5 scores.

The hierarchical clusters show overlap between 32 and 68, representing 42.9% of the population, whereas the overlap is more concentrated in the K Means clusters which occurs between 56 and 68 and accounts for 23.9%. The overlaps offer an opportunity to understand how students with the same aggregated WHO-5 score may receive support personalised to their wellbeing composition. Overlaps are analysed by considering the consistency of individual students' responses to highlight any strong sentiments by individual question. Consistency is measured using the standard deviation across students' five responses.

Looking at individual question scores, we know from previous results, that the question with the highest correlation to aggregated WHO-5 score is Question 1. Appendix Table 35 shows that the hierarchical clusters separate students who felt recently cheerful (Cluster 1) from those who did not (Cluster 2); the partitional cluster did not emphasise this difference. The analytics also clustered students with consistent scores within the overlap categories as can be seen in Figure 15. The difference between consistent and inconsistent scores is most clearly observable in the partitional clusters where students with varying scores (e.g. 5,0,1,4,5) are clustered with the students who have lower wellbeing compared to the students with consistent scores (e.g. 3,3,3,3,3) who have been clustered with students with higher wellbeing.

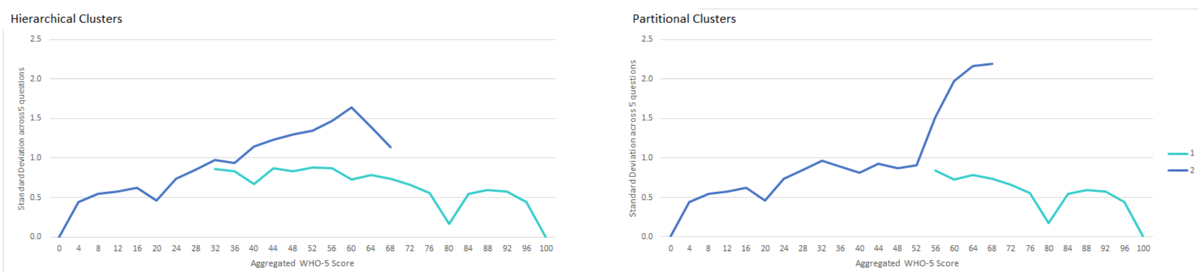


Figure 15 Standard Deviation Across 5 Questions by Aggregated WHO-5 Score and Cluster

To further illustrate this, Table 5 below shows, by individual question, four example students (A-D) who had a WHO-5 score of 56; this highlights the impact score consistency has on cluster segmentation. Student D has a high cheerfulness score and so, in the hierarchical process, was clustered in the higher wellbeing cluster however in the partitional approach their inconsistent answers result in them being clustered alongside those with lower average wellbeing.

Table 5 Example of cluster separation by question and answer for partitional approach

Over the last two weeks:	*Student A* *Cluster 1*	*Student B* *Cluster 1*	*Student C* *Cluster 2*	*Student D* *Cluster 2*
1. I have felt cheerful and in good spirits	3	4	2	5
2. I have felt calm and relaxed	2	2	5	1
3. I have felt active and vigorous	3	3	2	3
4. I woke up feeling fresh and rested	3	3	3	1
5. My daily life has been filled with things that interest me	3	2	2	4
Aggregated WHO-5 Score	56	56	56	56

This process was repeated for WHO-5 in March and May; results are included in Appendix 4: Clustering Analyses. The average Hopkins statistic across all three surveys was 0.523.

In addition to clustering static surveys, change in wellbeing was also clustered for students responding to multiple surveys. Using change in score as a continuous variable was used to assess impact on cluster tendency via the Hopkins statistic. Considering those who answered both September and March surveys (n = 2,621) the Hopkins score is higher than both baselines at 0.63. Including the change in their aggregated WHO-5 score from September to March as a percentage, increases the Hopkins statistic from 0.63 to 0.86. This result suggests that change in WHO-5 is better for clustering than one isolated survey however low data availability for multiple census points must be considered.

4.2.2. Clustering with additional data on known risk factors

Following the clustering of the WHO-5 data, the next step was to replicate the approach using risk factor datasets; firstly improvements in cluster tendency were measured (4.2.2.1) and subsequently the impact on cluster outputs were explored (4.2.2.2). Data on additional responsibilities had little descriptive properties and was not progressed to clustering; data on feeling part of the community had low comparative data availability (83.0% respectively compared to an average of 95.4% for demographic variables) and therefore was also not progressed to clustering.

4.2.2.1. Computing changes in the Hopkins statistic

Whilst descriptive analyses highlighted some statistical trends in the gender and fee status datasets, the Hopkins statistic cannot be computed for categorical variables and therefore the value that these data offer to the clustering process can only be assessed subjectively based on the descriptive trends and the extent to which it offers increased capacity to target or personalise relevant support.

For previous academic performance, the weak correlative results reported in the previous section do not necessarily suggest that the data is not useful for clustering. Considering the data numerically rather than categorically (“Count of failed modules” for example rather than “Failed modules Y/N” and “grade” rather than “classification”) means the Hopkins statistic can be computed. First, however, the Hopkins statistic must be recalculated for the continuing student population in isolation, to provide an accurate comparator baseline. The Hopkins statistic for continuing students' WHO-5 data is lower than the total dataset at 0.44 (compared to 0.52); adding previous academic performance data increases the cluster tendency of the dataset by 0.47 from 0.44 to 0.91 suggesting this information may be valuable when profiling student mental health data for continuing students at the start of the academic year.

The results by age found that there is scope to enhance the cluster tendency of the original dataset. Adding age to the original September WHO-5 dataset increases the Hopkins statistic by 0.31 (from 0.52 to 0.83). Similarly, despite the weak correlational relationship between VLE engagement and WHO-5, the inclusion of engagement variables in the dataset improved the cluster tendency of the March WHO-5 data by 0.31 from 0.52 to 0.83 and the May WHO-5 data from 0.51 to 0.84. The addition of the five CRM variables individually increases the Hopkins statistic for the dataset from 0.52 to 0.90; aggregating the five variables into one (i.e. a variable which accounts for a student having sought any type of support via the CRM) results in a lower Hopkins statistic of 0.69 suggesting that it may be useful to keep the data disaggregated at the variable level for the next clustering phase. The Hopkins statistic for May WHO-5 alongside CRM data increases from 0.51 to 0.92.

4.2.2.2. Exploring the impact on cluster segmentation

The opportunities of additional data on known risk factors are measured in terms of whether it improves standard WHO-5 segmentation via optimal cluster amount or the overlap range (size, percentage and observable trends). The results are summarised in Table 25 below. The trends column highlights and briefly explores which additional data was observable as a differentiator within the cluster overlaps.

Table 6 Summary of September Clusters using additional data on known risk factors

	Hierarchical				*Partitional*			
Cluster	*Optimal Clusters*	*Overlap Range(s)*	*Overlap (%)*	*Overlap trends*	*Optimal Clusters*	*Overlap Range*	*Overlap (%)*	*Overlap trends*
WH0-5 Data Only	2	32-68	42.9%	Individual question scores: Students with positive scores for cheerfulness tended to group with the higher wellbeing cluster despite lower scores for other questions	2	56-68	23.9%	Students with inconsistent scores across the five questions clustered with students with lower wellbeing
+ Previous Academic data (continuing students only)	2	0-64	48.4%	Previous academic performance: the clustering separated students with a WHO-5 score <= 64 with a grade of < = 61.	3	44-72	46.1%	Previous academic performance and individual question scores: Students starting academic year with grade average >67.6 clustered in the medium category. Students reporting low scores for question 4 clustered with the higher wellbeing students if cheerful > 4
+ Demographic data	2	0-100	100%	No distinct trends: Reduction in cophenetic correlation coefficient to 0.67 meaning clusters were not as distinct as when they were derived from mental health data alone	3[12]	44-80	72.2%	Age and gender: Mature male students (>21) clustered with higher wellbeing students if Q4 > 2

[12] As categorical data cannot be used in the computation of optimal K Means clusters using NBClust, both n=2 and n=3 were trialled based on previous results; the 3-cluster approach is represented here

The results above show that when adding additional data to the September WHO-5, the optimal clusters is between two and three. Both cluster types had higher proportional overlaps when additional data was added to the WHO-5 suggesting that profiles could incorporate more specific personalised trends when a wider dataset is used. In March and May the optimal number of partitional clusters was 3 in both cases and for hierarchical clustering was 4 and 8 respectively. This signals that, as the academic year progresses, the opportunities for segmentation and profiling increases.

4.3. Creating profiles from clusters

4.3.1. September profiles

Based on the outputs of the clustering process and the analysis of the overlaps, 9 September enrolment profiles were identified. These are listed in Table 7 below.

Table 7 September Profiles

Profile Identifier	*Overlap trends*	*Size of Profile*
SP1	Low Wellbeing (WHO-5 scores less than 44)	2,491
SP2	Continuing students averaging at least a 2:2 (WHO-5 scores 44-56)	990
SP3	Continuing students averaging at most a third class (WHO-5 scores 44-56)	556
SP4	Fresh and rested students (WHO-5 scores 44-56 inclusive)	27
SP5	Consistent across the five facets (WHO-5 scores 44-72 inclusive)	5,988
SP6	Inconsistent across the five facets (WHO-5 scores 44-72 inclusive)	261
SP7	Mature male students not feeling fresh and rested recently (WHO-5 scores 64-72) [13]	66
SP8	Achieving a 2:1, feeling cheerful at least some of the time (WHO-5 scores 68-72)	533
SP9	Positive Wellbeing (WHO-5 scores more than 72)	7,686

When the profiles are applied to individual students the results show that there are several opportunities to target and personalise support to students with the same overall wellbeing score; for example there are five distinct groupings for students with a WHO-5 score of 44 as can be observed in Table 8 below.

[13] Based on the large overlap for hierarchical outputs and the lack of exploration possible within partitional, it was concluded that the value of demographic data is limited within the current methodology and therefore only this profile was created to facilitate conceptual discussion in interviews

Table 8 Students scoring '44' on the September WHO-5 : Profile Deep Dive

	Student A	Student B	Student C	Student D	Student E
Profile	SP2	SP3	SP4	SP5	SP6
Age	29	23	19	24	20
Gender	F	M	M	F	F
1. I have felt cheerful and in good spirits	Less than half of the time	Less than half of the time	Less than half of the time	More than half of the time	More than half of the time
2. I have felt calm and relaxed	Less than half of the time	Most of the time	Less than half of the time	Some of the time	More than half of the time
3. I have felt active and vigorous	Less than half of the time	Less than half of the time	Less than half of the time	More than half of the time	At no time
4. I woke up feeling fresh and rested	Less than half of the time	Less than half of the time	Most of the time	Less than half of the time	Some of the time
5. My daily life has been filled with things that interest me	More than half of the time	Some of the time	Some of the time	Less than half of the time	Most of the time
Age	29	23	19	24	20
Gender	F	M	M	F	F
Previous Academic Performance	Continuing – grade average 68	Continuing – grade average 0	New student, no data	New student, no data	New student, no data
Average VLE logins	0.0	32.0	29.5	107.7	61.3
Average VLE time (hrs)	0.0	8.3	18.6	65.3	48.4

The results of the whole population mapping process are outlined in Figure 16 below. 54.7% of the student population fit within one of the two profiles at the extreme ends of the MHW spectrum (SP1 and SP9); the remaining 45.3% of respondents can be profiled for targeted and personalised support based on the other data available. Some of the profiles in the mid spectrum were large e.g. SP5 (n = 5988, 32.2%) whereas others were very small such as SP4 (n = 27, 0.1%).

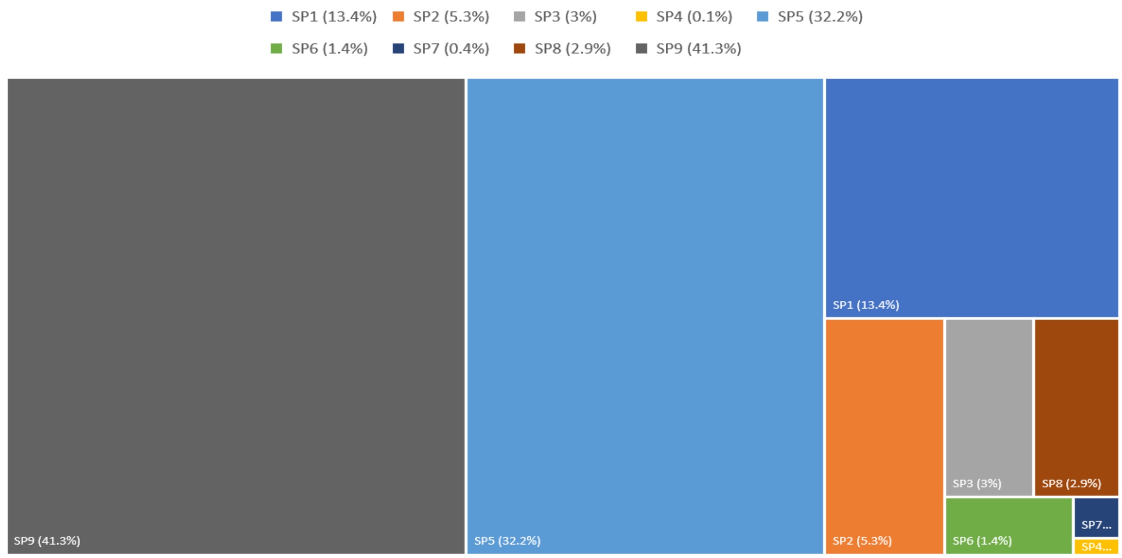


Figure 16 Tree map showing the size of profiles versus total responding population in September

4.3.2. March profiles

For the March clusters only partitional clusters (K means) were computed based on the results from the enrolment clusters which showed that the hierarchical clusters had little differentiation by MHW factors. Table 9 overleaf outlines the results which informed the profile creation.

Table 9 Summary of March partitional clusters

Cluster	*Optimal Clusters*	*Overlap Range(s)*	*Overlap (%)*	*Overlap trends*
WH0-5 Data Only	2 or 3 Analysis of indices inconclusive (see chart x) 3 used for clustering	At 32 At 60	11.3%	This cluster had two WHO-5 overlap points. The overlap at WHO-5 scores of 32 saw students differentiated just one student who scored 0 for Q1 and only 1 for Q2. Students scoring 60 were differentiated based on the consistency of scores (those scoring 3 “More than half of the time” for everything were clustered with the mid spectrum wellbeing cluster whereas those with at least one 5 “All the time” were clustered with the students reporting higher wellbeing.
+ VLE Data	3	0-100	100%	This cluster had very few observable wellbeing trends as evidenced by the maximum overlap rate and range. This was somewhat to be expected given the results from earlier in this chapter which showed a low correlative relationship between total logins and hours spent on the VLE and wellbeing.
+ CRM Data	2	48-52	10.6%	This cluster had a small and concentrated overlap range. Students scoring 48-52 were differentiated based on whether they had sought any sort of support via CRM and scored less than 4 for Q1; those matching this criteria were clustered with the lower wellbeing students whereas students reporting higher levels of cheerfulness or no support seeking behaviours were clustered with higher wellbeing students.

Based on the outputs of the clustering process and the analysis of the overlaps, 8 March profiles were identified and are listed in Table 10 below.

Table 10 March Profiles

Profile Identifier	*Overlap trends*	*Size of Profile*
MP1	Poor Mental Health (WHO-5 scores of 28 or lower)	1,204
MP2	Low Wellbeing (32 to 48)	513
MP3	Wellbeing deteriorated, no support sought (WHO-5 scores 32 to 68)	801
MP4	Change of Circumstances and Mitigation (WHO-5 scores 36 to 52)	95
MP5	Retained Enrolment Profile (WHO-5 scores 52 to 68)	175
MP6	Medium Wellbeing, Inconsistent Scores (WHO-5 scores 52 to 68)	33
MP7	Medium Wellbeing, Consistent Scores (WHO-5 scores 52 to 68)	413
MP8	Positive Wellbeing (WHO-5 score 72 or higher)	508

45.8% of students fit within the two profiles at the low and high end of the spectrum which is 8.9%pts lower than September meaning that the March profiles offer the opportunity to differentiate support for more than half (54.2%) of the responding population. MP3 is the second largest profile and looks to utilise data about students whose wellbeing scores have declined since September but have not raised any support enquiries with student services. MP6 was one of the smallest profiles across the three timepoints (n = 33, 0.9%) and looked at students who had varied responses across the five questions.

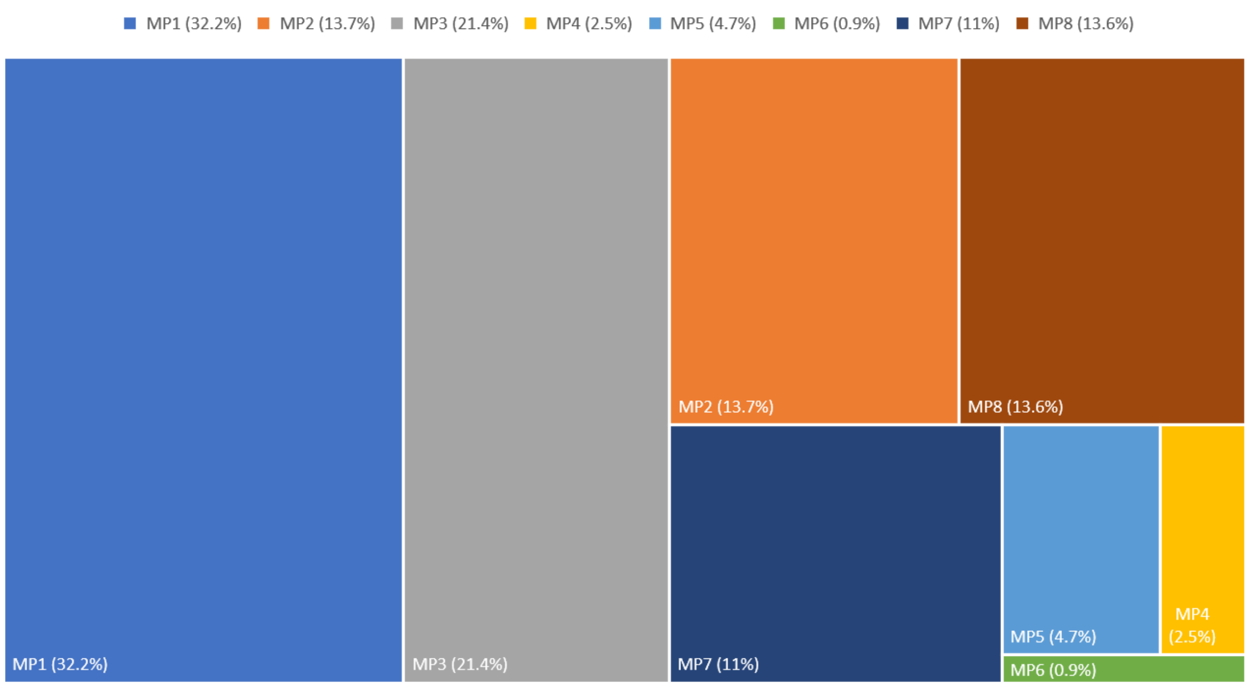


Figure 17 Tree map showing the size of profiles versus total responding population in March

4.3.3. May profiles

For the May clusters again only partitional clusters (k means) were computed; due to more students using and accessing online learning in semester 2 (see section for analysis) this reduced the overlap of the VLE clusters from 100% to 42.9% allowing for some separation of students by wellbeing and VLE usage. Based on the outputs of the clustering process and the analysis of the overlaps (summarised in Table 9 overleaf), 11 May profiles were identified and are presented in Table 12 below.

Table 11 Summary of May partitional clusters

Cluster	*Optimal Clusters*	*Overlap Range(s)*	*Overlap (%)*	*Overlap trends*
WH0-5 Data Only	2	48-52	11.2%	The overlap range here was focused mid spectrum however the cluster logic for the differentiation of students is unclear. 4 students scoring 48 were clustered with the higher wellbeing students and 3 students scoring 52 were clustered with the lower wellbeing students despite a lack of any anomalous WHO-5 responses.
+ VLE Data	3	28-44 60-68	42.9%	Similar to the March VLE Cluster there were no observable trends from an engagement perspective however this cluster did preserve more WHO-5 based separation than in March.
+ CRM Data	2	48-56	16.8%	Students with a score of 48 were separated based on whether they had initiated a Change of Circumstances case; if a student had not engaged with this process then they were clustered with the students reporting higher wellbeing scores. Students scoring 52 or 56 on the WHO-5 and who had enquired about change of circumstances or an assessment mitigation were clustered in the lower wellbeing cluster.
+ Semester 1 academic results	2 or 3	2 clusters: 44-48 3 clusters: 0-48 56-68 80	11.7% 80.8%	When considering a 2 cluster model, the data influences clustering with only a small overlap between 44-48; one student scoring 44 is grouped with students with higher wellbeing based on the combined score across Qs 1, 2 and 5 i.e. those found to have higher correlation with overall wellbeing. Similarly 15 students scoring 48 are clustered with the low wellbeing students based on their comparatively lower grades or lower responses to Q1.

Table 12 May Profiles

Profile Identifier	*Overlap trends*	*Size of Profile*
MayP1	Poor Mental Health (WHO-5 scores of 24 or lower)	703
MayP2	Low Wellbeing – no notable VLE behaviour (WHO-5 scores 28 to 44)	508
MayP3	Low Wellbeing – not very active on the VLE (WHO-5 scores 28 to 44)	322
MayP4	Low Wellbeing – very active on the VLE (WHO-5 scores of 28 to 44)	191
MayP5	Medium Wellbeing: Minimum of a grade 60 and no failed modules (WHO-5 scores 48 to 68)	202
MayP6	Medium Wellbeing: No engagement with CRM (WHO-5 scores 48 to 68)	352
MayP7	Medium Wellbeing: increased over time (WHO-5 scores 48 to 68)	119
MayP8	Medium Wellbeing: decreased over time (WHO-5 scores 48 to 68)	108
MayP9	Medium Wellbeing: Often cheerful (at least more than half of the time) despite wellbeing decreased over time (WHO-5 scores 48 to 68)	108
MayP10	Medium Wellbeing: no additional profiling (WHO-5 scores 48 to 68)	171
MayP11	Positive Wellbeing (WHO-5 score of 72 or higher)	702

40.3% of students fit in to one of the profiles (MayP1 and MayP11) which are at the extreme end of the wellbeing spectrum. The remaining 59.7% of the population in the mid-range could be offered targeted and personalised support based on other data e.g. students with low wellbeing who are not active on the VLE (MayP3, n = 322) could be offered or signposted to different support to those frequently using the VLE (MayP4, n = 191). The smallest profiles were MayP8 and MayP9 (n = 108 in both cases).

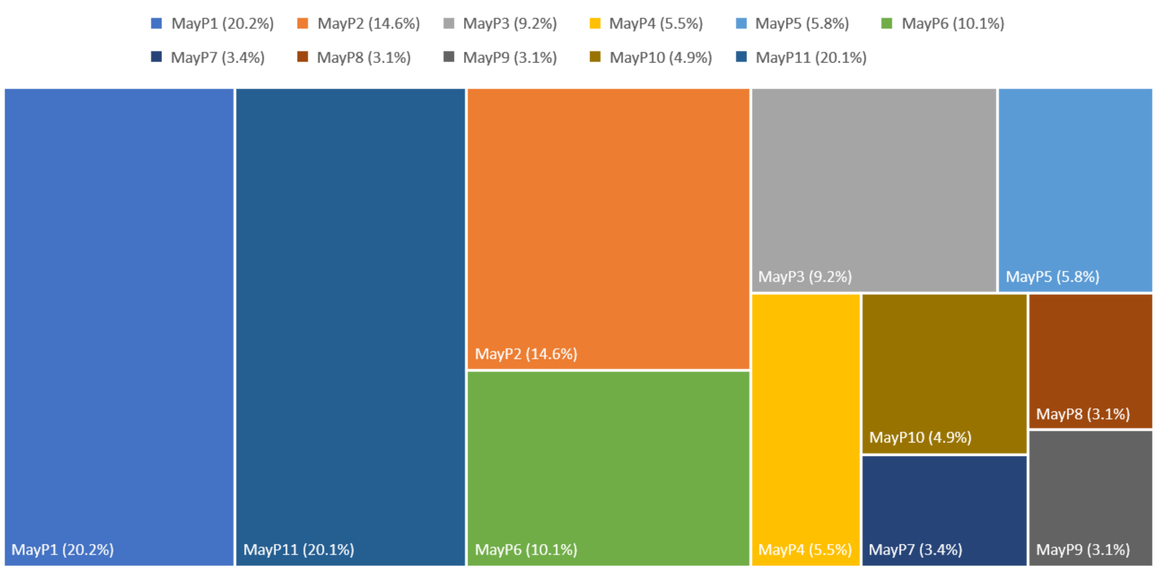


Figure 18 Tree map showing the size of profiles versus total responding population in May

4.4. Presenting profiles to university support staff to discover how they may be used in practice

This section presents the qualitative results garnered from multiple interviews with participants working in a university CMH team. Firstly, 4.4.1 explores staff perceptions of the role data plays in their current practice and how their current service is delivered with respect to targeted and personalised MHW support. The data from the quantitative analysis was presented to help prompt discussion. Secondly, 4.4.2 presents data on participants' perceptions of the opportunities and risks of SMHP with a more detailed and situational investigation of their reactions to the real profiles created in this research presented in 4.4.3. In addition to commentary on the utility and validity of the profiles, participants offered examples of how they might use them; these have been recorded and translated into use cases and are presented in 4.4.4. Combined these sections, detail how such profiles may be used in practice by university support staff to deliver a Whole University approach to student mental health (RQ2).

To preserve anonymity the interviewers are referred to using codes and are differentiated between whether they are a service leader (SL) (whose focus includes both holistic and student-level service delivery) or a practitioner (PR) (student-level only). The samples are as follows:-

- SL - Service leaders (n = 2)
- PR – Practitioners (n = 4)

4.4.1. The role of data in targeted and personalised student mental health support

In investigating how might staff implement data-driven SMHP as an approach to delivering their service, the first aspect to explore in the interviews was data availability, access, usage and scope along with participants' perceptions of their own data literacy. All six interviewees reported that they use data in their current role although the types of data they used and preferred varied. Practitioners were content with the level of data they had access to even though it was described by several as 'basic'; the following data sources are a complete list identified across participants:-

- Service registration form data (survey completed by every student who self refers)
- CRM support data
- Data from clinical tools e.g. GAD-7, PHQ-9
- Data from external agencies e.g. the NHS
- Qualitative data resulting from the initial meeting and assessment
- Internal service dashboards

Despite a lot of student data being available at point of self-referral e.g. name, age, symptoms, there was little data informing the needs of the entire population; when asked how the service identifies and develops support one participant said *‘We are led by what practitioners say around where gaps are and what are the most common issues for students’*[SL]. Notably not one interviewee said they had used WHO-5 data in therapeutic situations in their current or previous roles. Perceptions of the WHO-5 was that its benefits were its brevity which they speculated meant more students will engage with it. They liked the positive positioning of the questions but most were sceptical of his ability to perform as well as a diagnostic tool such as the GAD-7 and PHQ-9 and noted any tool has limitations if the student is worried about disclosure. One interviewee suggested that ‘*one of my concerns with the WHO-5 would be that students needs wouldn't be fully or accurately assessed based on it.’* [PR] suggesting a preference for clinical tools for those experiencing mental health difficulties.

It was acknowledged that none of the tools would capture all the risks however data was used by staff to gauge severity via the self-referral form. When asked whether students were surveyed as a possible route to understanding their needs or to targeting and personalising support the only tool acknowledged was the service registration form which notably relies on the student first enquiring with the service and is thus very reactive. An interviewee noted; *‘I worked in another organization and we would survey the whole population and find out a little bit more about what their needs were and use data to plan activities’* [SL]. However the same person noted some risks to this approach, advising caution about assuming students understand their own needs and what the university can offer, citing this as the reason it was not deployed in the current team.

Service leaders had a vision for getting more data to inform the service’s activities; ‘*My ambition is that any student coming into the service isn't coming with us not knowing anything about them*’ [SL]. They also suggested that if they had more information they would use this to expedite the student into therapeutic delivery if appropriate which was supported by other participants. There was a perception that data is also useful for planning and evaluation as well as university level analysis. One senior member of staff also suggested that data will be used for auditing purposes and to influence future policy especially in terms of sector comparisons. Having the right data and knowledge to target support was mentioned in relation to new interventions in the portfolio;

> *'We've just started a workshop around burnout because we know that students don't recognize when they're reaching burnout so can we give students some psychoeducation that can help them better manage their wellbeing. We just can't target this so have to offer it to everyone'[SL].*

Despite access to a variety of datasets, there was little targeting of MHW support to students; when asked directly whether the service actively targets students for support, Interviewee1 replied '*I don't think we do. Currently, we just sort of advertise the service and hope students come to us [...] it's like an old school kind of prevention model".*[SL] Another participant described it as '*a blanket approach'* [PR]. It was noted that the wider service does target support around Widening Participation themes such as Equality, Diversity and Inclusion but limited to learning and teaching support rather than wellbeing. Mental health was not something which was used to identify students in need of support other than reactively to support reasonable adjustments for assessments where it was declared by the student. Data was however used in other ways to influence service delivery. One interviewee discussed how they adapt the clinical tools, selecting some questions and not asking others e.g. speaking of the suicidality question on the Beck Scale, '*I never use that question because I just think it's just a minefield of problems that it could cause, depending on the students difficulties*' [PR]. Despite dextrous use of the tools to design and nuance therapy, practitioners did not consider using the data for holistic service design to be part of their role and one remarked '*Data analytics tends to be a rung above me'* [PR] suggesting that it is more aligned to management.

Practitioners articulated their responsibilities for intervention based on a spectrum of mental health. Psychological Wellbeing Practitioners (PWP) were described as working one on one with students and also sometimes in groups to deliver non clinical therapeutic support such as students struggling with generalised anxiety disorders, sleep issues and stress. Their treatments often involve Cognitive Behavioural Therapy (CBT) and other forms of psychoeducation; aimed at those on the middle of the spectrum, practitioners suggested that data driven targeting and personalisation didn't feel like it fitted within the remit for PWP support but were unable to suggest how such a large group of students may be identified without self-help seeking. This sentiment was echoed by participants when considering roles which operate on the more extreme end of the mental health spectrum (e.g. qualified mental health nurses or counsellors). It was felt that students exhibiting particularly acute mental health issues such as suicidal feelings, clinical depression and anxiety required 1-1 interventions like talking therapies and were required to approach the service to receive such support rather than proactively targeting students.

There were some perceived barriers to targeted MHW support. The first can be summarised as agreeing what 'targeting' means; service leaders understood it to be university level whereas most practitioners assumed that targeting related to their existing caseload rather than an approach aimed at non-service users. The second challenge was a perceived increase in workload; *'it would be very resource heavy to try and physically contact students in terms of ringing them. You might miss them. They might not ring you back'.* [PR]. A service leader noted that the service was already stretched to capacity in the current working model but was optimistic that the approach may actually help manage demand issues especially if automation was built into the process. Furthermore a practitioner also suggested that targeting with data could help prioritise need and risk.

It was noted by multiple participants that students making the first step to seek help is a key part of support and that targeting interventions at individuals may not fully address the need for this in successful therapy. This was considered an influencing factor in whether and to what extent the service could and should adopt a more proactive approach; '*we could send an email and say, "come to our service", but if they're not intrinsically motivated to do that, then they're never going to come to your door.*' [SL].

Service leaders considered it as an aspiration to take a more targeted approach; one said *'at the moment we're a reactive service and I'd really like to see us being proactive'* [SL] whilst the other had previous experience of working proactively in a mental health organisation and valued *'the ability that proactivity can have for designing and planning the service'* [SL].

Moving to a more proactive service was considered to be both advantageous but also problematic. It was felt by several that the needs of the student couldn't always be realistically met even when working proactively either because the specific need of the student doesn't exist within the current university support framework which, it was felt, data cannot help with. A practitioner said *'It all comes down to the barriers for students seeking support. If the barrier is just that they don't know you exist then maybe proactive support would be good'* [PR]. The little proactive mental health support that is happening was found to be generic and population based rather than 1-1 or group level support; '*we use Open Days and the Students' Union for reach and scope and work with them to offer services like workshops. We don't necessarily target- it's offered to all students'* (PR).

In addition to these activities the only other proactive activity taking place in the service currently was email 'nudges' which were considered a '*less intrusive*' [SL] form of proactive contact than interventions such as a phone call. Again, the possibility to target those emails was still in its infancy and little was known about this activity at practitioner level however one was aware and said;

> *'Nudges. There's a term that's been thrown around! I think they serve a real purpose. If we can highlight that a particular student is showing distress or deficits in certain areas then there's the opportunity to offer the support. I think it's a really great thing'[PR].*

It was understood that data and nudging activities could help personalisation as well as targeting. As with the term "targeted support", "personalised support" was also considered to mean internal to the service and didn't extend to students who weren't engaging with mental health services. The opportunities of personalising communications were considered positive; '*in general people probably do like a* *personalized approach. Nobody likes to receive a blanket email for example, do they? You might be more inclined to ignore that.*' [SL].

Once the student was in the support system there was agreement amongst interviewees that services were personalised and '*bespoke*' [PR] from the earliest stages of the process. As students are often unknown to the service before enquiry, triage represents the second opportunity to personalise students' treatment after the initial self-referral form. Interviewee2 reflected that this process is not always accurate as nearly half of students are allocated to mental health practitioners via the form and then subsequently redirected to counsellors after the first appointment. Similarly, Interviewee 1 described the process as being like *'matching them or signposting them to the support that we think best meets their need and that's really based on conditions and judgements in the moment'* [SL]. That may be personalised but relies on a level of subjectivity which data driven approaches attempts to avoid.

The therapy itself then generates further data in the form of qualitative conversation. This wasn't considered by all to be an efficient use of time and a barrier to support in the early sessions; '*the first therapeutic meeting with any of our therapists is really wasted in terms of gathering information, whereas it would be so much easier if we had more information beforehand*' [SL]. However practitioners believed that conversational data and comments made by the students in therapy sessions was the data they considered most relevant to personalising therapy and intervention design; '*that's when we get a clear idea of what's going on. That other data [profiles] can be used around framing practitioners' curiosity but conclusions wouldn't be drawn until we're in session together.'* [PR].

4.4.2. Perceived opportunities and risks of profiling students' MHW

To identify propensity for implementing data-driven SMHP, the second part of the interviews delved into the participants' perceptions of the opportunities and risks of profiling students based on MHW factors. Participants referred to the presentation which was given prior to the interviews as being useful for their understanding of the term profiling as an approach which seeks to group students based on common traits. Staff preferred the term *groups* rather than *clusters* and were hesitant to talk about clusters.

Service designers were optimistic about the opportunities that profiles could offer to targeted and personalised nudging to encourage students to engage with the support that is on offer at the university;

> *"This is like nudge theory. Gentle reminders because actually it's that whole thing about motivation. […] If somebody was gently nudging you towards a goal, you know the third time you get that nudge, you might say, "right? This is the reminder that I need. I'm going to do it. That's it. I'm registering" [SL]*

For the service leads, the link between profiling and targeting or personalising support was clearer than for practitioners; '

> *'When you look at clinical tools, it's more on the intervention side, whereas if you're looking at how can you target certain populations of students, you're going to have to look at all of the other data and then, once you get them through your door, it's about using the clinical tool to see where they're actually at.' [SL].*

Practitioners often started their reflections on profiles by focussing on if and how they may influence their 1-1 therapies rather than from a service perspective. Practitioners felt they were already creating profiles through their own practice by using their agreed suite of clinical tools alongside their experience. This tended to form a pattern amongst the practitioners that regardless of their thoughts around profiling as a general approach, data driven profiles derived from anything other than standard clinical tools were not essential to their role when compared with more traditional forms of assessment;

> *'I suppose I sort of profile myself if that makes sense, because from doing the interview and the assessment you can more or less gauge what type of anxiety a student has or whether it's low mood and anger by getting the information and talking to them' [PR]*

One practitioner described the process of profiling as 'jarring' with their professional point of view and questioned the extent to which students were aware of the activity and consented to the data being used in this way. When asked if they would ever use the profiles only one explicitly called out ethics *'there would need to be more training. I definitely would want to know that it was valid and ethical'* [PR] although another suggested that the approach of contacting students based on their low profile seemed like an *'infringement on their right to be miserable'* [PR]. This practitioner questioned how prescriptive the resulting intervention would be; '*There's a process for people finding their own way to support. How far would you take this? Would it almost be like 'you must come in'?' [PR].* This practitioner also suggested that profiling 'freaked her out' and suggested she may be 'naïve' in terms of how algorithms could be tailored to students based on things like their usage of the student portal. All suggested that validity, efficacy and best practice would need to be established as it was considered an experimental type of activity not yet embedded in standard counselling or wellbeing services.

Amongst practitioners it was suggested that profiling would sacrifice specificity and personalisation although this was predominantly with regards to therapy rather than the wider service; *'I don't feel like there will ever be a tool that will encapsulate the human experience'* [PR]. That said this particular participant further suggested that profiling can produce 'gateways' which are useful in highlighting certain areas of distress and allow therapists to offer opportunities that may not otherwise have been apparent after several sessions. There was a feeling that profiles would likely miss something important or would be misled by anomalies in the data that could invalidate the process; 't*here's always going to be contextual factors and you are always going to get those anomalies that contradict what you know about the whole of your dataset*' [SL]. Interviewee 2 said;

> *'With profiling you could end up with it clustering anomalies in your data simply because they are there. They're looking for a thread of commonality but actually it could just be that*

they [the student] just didn't feel fresh on that morning, because they'd had a rubbish night.'[SL]

This suggests concern that the clustering algorithm is susceptible to 'anomalies' and is capable of making its own decisions on the data. It also suggests the profiles are using transient data, only relevant to the particular moment the survey is completed, to make longer term judgements about the student. One was particularly keen to know that profiles wouldn't be 'final' as they speculated there may be students in the positive wellbeing category who didn't truthfully answer. Interviewee2 suggested that '*mental health intervention is already so personalized. Once they've got to the front door, you need that clinical judgment around what's going to be the best support for this student.* [SL].

There was a preconception amongst all practitioners that profiles were in some way trying to 'predict' outcomes rather than to describe current behaviours;

'You've got to be really careful not to use things like this as a predictive measure […] I used to use the Beck Scale which is a good tool to cluster people into high risk and low risk but it can't predict anything' [PR]

All participants agreed that regardless of the profile they "should be treated with caution"[PR] and that the timing of the data for informing profiles was very important. When presenting some of the descriptive data outlined earlier in this chapter one participant noted;

'September data doesn't give you a picture of what would be quote, unquote, normal, or a regular status quo for somebody's wellbeing because enrolment is a particular point in their journey. For example, if you took a snapshot of somebody's wellbeing on their wedding day, you know it's very different to what their normal status quo would be.' [SL]

Other participants also noted that if profiling were to be effective it would require regular data monitoring to ensure that the information being acted upon was up to date and correct as profiles would struggle to keep up with natural fluctuations in students' mental health. Seasonal timepoints referenced included Christmas and examination time which were key points when practitioners said they experience spikes in demand for their services.

4.4.3. Reflections on the profiles identified in this research

The final aspect of the interviews sought direct feedback on the profiles presented to participants in the presentation; by giving staff real examples of profiling the intention was to prompt their views on how they might use student MHW profiles in practice.

Profiles using aggregated WHO-5 scores were seen to be very useful to both practitioners and service leads but typically only for students reporting lower scores; “we’d want to be targeting those ones definitely.”[PR]. It was suggested to adjust the threshold for what is categorised as “low wellbeing” throughout the academic year based on seasonal fluctuations in mental health and the perception that the enrolment baseline is likely inflated. The opportunities for using additional data to supplement aggregated scores was noted by several participants; “looking at the total WHO-5 score that's the only information that you've got to go on and that's quite crude. So I guess if you've got further information that builds a bigger picture around that WHO-5 score then that's going to help you, especially if you're talking about tailoring interventions or maybe targeting then you know you would need to have that extra information and treat them a little bit differently.”[SL]. When considering negative profiles two practitioners reflected on known risk factors which were not included in the profiles including finance (which did not have a high impact on clusters in the previous analysis) and disability.

The positive wellbeing profiles received mixed reactions as there was disagreement on whether these students should be monitored or even considered by the wellbeing team. One practitioner advised that students with positive wellbeing rarely required therapies and if they did the intervention would be brief. Service leaders were divided on whether these profiles represented an opportunity for proactive and targeted 1-1 support but both acknowledged that there may be opportunities as part of a 'whole university approach to mental health' which was mentioned explicitly. Practitioners working on a broader scope of mental health problems were particularly optimistic about how institutions could learn from those positive trending students suggesting that positive profiles were useful for students who had past experiences of poor mental health and were trying to get ahead of anticipated struggles and stresses such as assessment time.

In terms of profiles which look at the underlying WHO-5 scores, SP6 which considered fluctuations in sub-scores, was the profile most linked with personalisation and enabled more relevant interventions based on students' specific needs; 'if you could extract it out as to where the dip was in their score, you could definitely look at targeting intervention or reaching out to the student' [SL]. This interview suggested specific examples where the WHO-5 question around feeling fresh and rested might be linked to signposting interventions for sleep and wellbeing workshops. It was also suggested that considering fluctuations in individual scores was a good indicator that the student had considered the facets of wellbeing carefully rather than just 'clicking three for everything' [SL]. However, others felt that there could be quite a lot of variables impacting individual questions which would be difficult to interpret cold. As these profiles were so small in terms of proportional size, interviewees thought that it would be feasible to do 'deep dives' into these students' wellbeing suggesting profiling as a means to cater for smaller groups. Conversely, the proportional size of some profiles e.g. SP4 (n = 27) was considered problematic considering the lengthy and complicated process of profiling, nevertheless the idea that something bespoke could be offered to those students was considered a worthwhile compromise, particularly if the process could be automated.

Only one profile was created using the demographic data available and it was juxtaposed with an individual question score: SP7 Mature male students reporting low scores for feeling fresh and rested. Only one participant, who was generally most curious about the data, found this profile interesting. Others felt that demographics may influence students' interpretation of the WHO-5 questions and so they weren't sure how this would translate into effective intervention. Another concern was around targeting interventions at this group causing unintended concern with students feeling ‘singled out’ based on their age which was considered intrusive.

Profiles which considered changes in mental health were the most contentious; the majority of participants suggested that the time periods between September and March and March and May were too long, hindering the usability of these profiles. Furthermore, because they didn’t offer relevant context sufficient to infer causality, they were felt to be difficult to act upon. They were also seen to feed a culture of lowered resilience where MHW fluctuations were unduly amplified and disproportionate; ‘The problem with these is that we don't want to pathologize things. [...] Even in the general population, wellbeing will fluctuate up and down. We need to be normalizing that.’[SL].

The profiles around students’ engagement with support services had some perceived positive opportunities but also led interviewees to speculate on the impact it could have on student resilience. When discussing MP3 “Wellbeing deteriorated but sought no support” one said; “I do think they’re useful [..] 801 students have deteriorated but not had any support. Maybe it's just about reminding them of the support that's there.”[PR]. However this was seen as problematic by one of the service leaders when discussing a similar profile, MayP6 “Medium Wellbeing: No support sought”;

> *“What we don't want to do is end up with thousands of students all of a sudden saying we need a counselling service because I don’t feel good all of the time. They haven’t asked for help but that could mean that their functioning side of things is OK, they’re resilient and capable of self-care. Maybe they didn’t seek support because their coping strategies have kicked in.”[SL]*

The profiles which considered previous academic factors were treated in two different ways based on assumed causality. One perception was that if the low wellbeing was impacting scholarly performance then the intervention is more suited to an academic tutor. However many of the practitioners also considered the impact that a bad grade or failed module could have on wellbeing and agreed that it was a useful profile to consider at certain points in the academic calendar such as grades release time. Interestingly this was lacking in the literature review on risk factors. Furthermore, one practitioner [PR] identified that wellbeing may come ‘at a cost’ for academic achievement, suggesting these profiles ‘run counter to some of my own experiences of student mental health’.

Similarly, profiles highlighting particular VLE behaviours were regarded as one of the more interesting profile types as it clearly aligned to the students’ core experience. However it was acknowledged that the service had no interventions designed around either low or excessive VLE engagement. Furthermore, Interviewee 4 suggested that many students’ perception of their online engagement is misaligned to programme requirements. Again, some suggested that this type of intervention may be better suited with the academic team regardless of whether it had a wellbeing aspect; ‘tutors should know how to signpost students if they feel there is a risk greater than just academic engagement’ [SL]. However, they suggested that VLE login data, rather than mental health profiles, would be more appropriate to share with academic colleagues. Interviewee 1 did note that this profile may influence how and via which platforms the service is promoted suggesting that students in profiles indicating low VLE activity may be targeted for an additional follow up telephone call as they may miss the online prompts.

4.4.4. Use cases for student mental health profiling (SMHP)

Although some interviewees had serious concerns about the risks associated with profiling, all made an attempt to consider and discuss the possible use cases for profiling with respect to their role and their team. The service designers were very optimistic about using profiling in their service design however Interviewee 4 and 6 saw very little value to them in their roles and couldn’t see themselves using the profiles to inform their therapy or approach, highlighting the WHO-5 tool rather than the profiling as the reason for this; ‘*I'm not saying I’d never use these profiles but I've never used The WHO-5 and so at the moment I can do my job without it.*’ [PR].

Interviewee 3 and 5 shared that, although they didn't feel like they would use all of the profiles, they were interested by some and could see this influencing the conversations that they had with students. Interviewee 5 also expressed that they felt the change from one profile to another over time was as important as the profile itself, suggesting a need for continual monitoring.

Table 13, lists the potential use cases for student mental health profiles as perceived by the staff trained in student mental health and wellbeing. Some use cases represent the benefits that profiling can offer to administrative tasks such as better planning and reporting whereas others relate to direct interventions with students. The type of intervention and level of support is important to the discussion of roles and responsibilities in the next section therefore Table 13 includes columns to show whether these are direct interventions (for individual students or profiles) or indirect interventions as part of a whole university approach.

Table 13 Overview of use cases identified for student mental health profiles

Use Case	**Intervention Type**	**Level of support**
U1 Personalising support e.g. communication, therapy	Direct	Individual or profile
U2 Targeting support e.g. workshops, therapy, self-help articles		
U3 Delivering prevention as well as intervention		
U4 Raising awareness of the service		
U5 Managing risk and prioritising some students over others		
U6 Improving existing understanding of the whole student population	Indirect	Whole University
U7 Designing new interventions to meet students' needs		
U8 Informing service planning regarding policies, resources and portfolio		
U9 Monitoring impact on wellbeing outcomes from an established baseline		
U10 Evaluating the differential impact of the service and interventions		
U11 Facilitating sector comparisons		

4.5. Summary of results

4.5.1. Summary of the data, clustering and profiling process

WHO-5 data in isolation is not highly clusterable with an average Hopkins statistic across the three surveys of 0.523; some nuance at the question level may however facilitate the creation of profiles which have value for targeting and personalising support. Adding supplementary data to contextualise the WHO-5 scores increased the tendency for clusters. Table 29 (overleaf) summarises the process with respect to the following three facets to inform a discussion on their appropriateness for clustering and profiling:

- Hopkins statistic (if available)
- Descriptive trends garnered from statistical analyses
- Data availability

Table 14 Summary of dataset properties

Data	Hopkins statistic			Descriptive trends	Data availability	Used in clustering?
	Sept	**March**	**May**			
WHO-5 Survey Data	0.54	0.52	0.51	Population and question level insights	100%	Yes
Age	0.83	0.79	0.85	No clear or strong correlational relationship between the two datasets (R2 = 0.23)	90.2%	Yes
Gender	N/A – Cannot be computed on this type of variable			More female students and students of ‘other’ gender reporting low levels of wellbeing	99.4%	Yes
Fee Status				International students were significantly more likely to report positive wellbeing	96.5%	Yes
Community				Students feeling part of the community have, on average, higher WHO-5 scores	83.0%	No
Additional Responsibilities				No observable trends in the data	83.3%	No
Previous academic achievement	0.91	N/A	0.88	Previous academic achievement did not show many trends with wellbeing for continuing students at enrolment however on average students carrying failed modules from Semester 1 have lower average WHO-5 scores	54.6% for September; 77.9% for May	Yes

Table continued…

Data	Hopkins statistic Sept	March	May	Descriptive trends	Data availability	Used in clustering?
VLE engagement data	Not available at this survey point	0.83	0.84	Very little in terms of correlative relationships between variables and WHO-5; more emphasis on login activity rather than hours spent	100%	Yes
CRM engagement data		0.90	0.92	Highlighted noticeable trends around the Change of Circumstances process	100%	Yes
Change in WHO-5 Score from previous survey		0.86	0.75	Identified a great wellbeing decline between September and March;	13.3% for March; 20.2% for May	Yes
Combined WHO-5 Score (3 surveys)			0.66	Identified majority of students experience fluctuation across wellbeing label boundaries	4.4% (n = 899 / 20,468)	Yes

The clustering of WHO-5 data resulted in two distinct groups in September and May and for March the statistical tests suggested that 2 or 3 was a viable amount. The overlap points were different for each survey and changed when supplementary data was added. Even when adding supplementary data, the optimal number of clusters was either 2 or 3.

The clusters overlapped between 32-68 in September with more concentrated overlap points in March and May. Although a hierarchical procedure did produce clusters, only the partitional approach preserved the core MHW characteristic generated from the WHO-5 data. There were no student mental health commonalties in the hierarchical clusters rendering these ineffective for use in creating student mental health profiles. The initial analysis on the hierarchical clusters for the September dataset showed that this approach was less effective than the partitional approach in producing discrete student groupings; it was not progressed to the later analyses for the March and May datasets. Those wishing to replicate a cluster-based methodology to create student mental health profiles may find that Hierarchical clustering is not appropriate with WHO-5 data.

Based on the clustering outputs, 28 profiles were created; 9 profiles for the September dataset, 8 for the March dataset and 11 for the May dataset. These profiles differed at each point based on data availability, cluster sizes and defining characteristics. These profiles segmented students with the same overall WHO-5 scores into smaller groups to facilitate more targeted and personalised support. This hypothesis was discussed qualitatively with university MHW staff to understand the real benefit of these 28 profiles and of the approach generally; the results are summarised in the next and final section of this chapter.

4.5.2. Summary of staff perceptions of the validity and utility of student mental health profiles for targeted and personalised support

The interview data showed there was already a large amount of data available to incorporate within existing therapies and interventions but very little activity for non-service users. In terms of understanding the opportunities, challenges and implications of targeting mental health, participants juxtaposed notions of a proactive service with roles, responsibilities and existing resources. Participants had mixed views on profiling; some saw the benefits and cited a variety of use cases for profiling whereas others felt it was not in keeping with their traditional practice. Profiles based solely on the mental health score profiles and those utilising data from the VLE and CRM were perceived to be more impactful than demographics profiles due to an unclear idea of the resulting actions and activities that the latter may require. Eleven use cases for student mental health profiles were identified for both direct and indirect service design and delivery.

5. Discussion

This exploratory study shows that it is possible to construct student mental health profiles using WHO-5 data and that these profiles can be nuanced by supplementary data on known risk factors. Moreover, when profiles were presented to staff this research has shown that this data was perceived to be useful to mediate the opportunities and risks associated with providing mental health support to students, but most staff saw this process as a complement rather than a supplement to existing provision of healthcare support in a university setting. Specifically, this tool was shown to be capable of providing a hierarchy of student support need which was deemed useful for service design but profiles were not considered appropriate to replace one to one triage or therapeutic support.

The need to develop such tools derives from documented increased rates of mental ill health disclosure amongst the UK student population; there are still many students not receiving the support they need and university services are often stretched to capacity and forced to operate reactively. There is great emphasis on the need to embrace technology and deliver data-led student mental health support for *whole university* populations, however there exists a gap in our understanding of how this may be achieved in practice which is a key challenge of HPU approaches (see 2.1). This research has added specificity to the promotion of health and wellbeing support by identifying profiles and use cases which can be applied across the whole population. The profiles challenge some of the existing cutoff points for the WHO-5 (Sischka et al, 2020) by proposing a profiling approach which considers multiple facets of the student experience, not just the WHO-5 score.

Studies often focus on measurement via diagnostic tools thus failing to capture changes in students wellbeing or screen a whole population and there is little research to guide our understanding of what may be appropriate for all students at multiple census points. Similarly, once captured, how may this data be used ethically and intelligently and how do staff consider its application as part of a more proactive and efficient service which targets and personalises interventions are areas where previous research has not yet explored. This research therefore provides a necessary first step in maintaining dialogue in the sector on such issues by presenting an approach to understanding service design through the lens of profile-based data-driven student mental health support. Staff viewed this tool as applicable to the whole student body not just those already at risk and in relation to proactive as well as reactive support. This is important considering that current constraints on university services are not proportionate to student needs.

Despite these findings, there are several considerations including data availability, ethics and privacy and the analytical methodology for profiling students via clustering, as well as the impact of profiling on staff within current team structures which this chapter addresses. The discussion is structured based on the two research questions;

RQ1: How can student mental health profiles be created using WHO-5 data and data on known risk factors?

RQ2: How might university student services staff implement mental health profiling as a Whole University approach to targeted and personalised mental health and wellbeing support?

5.1. Student mental health data, clusters and profiles

To understand how student mental health profiles can be created, this section explores viability of the WHO-5 data (5.1.1) to assess its value compared to other measurement tools identified in the literature (2.2.2). The section then discusses how additional contextual data influences the profiling process (5.1.2) based on the known risk factors identified in the literature (2.2.3). This includes consideration of the mechanisms and timings for capturing mental health data (2.2.1) as well as students' propensity to share their data in light of the literature on surveillance and trust (2.4.3) and the extent to which the process facilitated the creation of homogenous student groupings which is a key enabling factor of targeted and personalised support (2.4.1). This section concludes with an analysis of the benefits and disbenefits of cluster-driven profiling (5.1.3) compared to the alternative profiling approaches reviewed in the literature (2.4.2).

5.1.1. Availability and validity of student mental health data

The results of this study found that 81.1% of students completed a short, five-question wellbeing survey at enrolment which is consistent with the literature which suggests that students will share their data where consent and intended use is explicit (Prinsloo and Slade, 2015). Additionally, they consented to share their personal results with their university for analysis alongside other variables and potential follow up actions by the student support team. This is consistent with literature suggesting that the majority of students trust their institution with their personal data (Jones et al., 2020; Tsai, Whitelock-Wainwright, and Gaŝević, 2021). Whilst the response rate figure dropped significantly throughout the academic year (firstly to 11.5% then to 10.3%), this initial level of participation was representative of both age and gender, and suggests only a minority group will withhold disclosure. Having evidence of such large-scale participation is important given the need to build on small scale, exploratory studies and facilitate action aimed at tackling poor student mental health across the whole student population. The literature review identified only a small number of examples where studies had achieved a significant of more than 20% response rate with an average sampling population of < 3000 (Harrer et al., 2018). The WHO-5 tool itself is much shorter than other clinical surveys used within self-selected populations, and therefore it's brevity and non-invasive format may be influential in the high volume of students engaging. The first crucial finding therefore is that it is achievable to representatively screen a majority proportion of a university population using the WHO-5 data collection tool.

The literature identified that a key challenge for improving students' mental health and wellbeing was a lack of awareness of their problem coupled with a lack of understanding about the solutions available to them via their university. This is further compounded by students' lack of propensity to seek help due to their perceptions of the support offer and the stigma of disclosure (Eisenberg et al., 2009; Thorley, 2017). This research has found that even with an optimal data capture methodology (i.e. in September which achieved over 80% responses rate), there will still be a large proportion of students who do not share their data with their institution to facilitate proactive support. Therefore the proportion of students within this subpopulation who match a risk profile (e.g. SP1) may be in immediate need of mental health support but they remain unknown to the service. By assuming the same distribution of scores as the responding population, we could estimate that there were a further 581 students (13.4% of 4,338) who would be grouped with students reporting scores lower than 44 (SP1) and thus eligible for targeted SP1 interventions. However, this is an assumption only and the real distribution of low wellbeing maybe higher, due to stigma, or lower if the proactive capturing of data is removing a barrier to disclose. When using a self-reported metric, the true characteristics of the non-respondents can never be known without mandated mental health data capture. This itself is problematic and may well be considered a violation of individual privacy as it may not actually address the issue of identifying real issues if students do not feel comfortable answering truthfully.

Furthermore, capturing the data may also pose as an intervention which positively impacts both students' awareness of the problem and where to go for help. For example, students may complete the WHO-5 survey and come to the realisation that there score is low or lower than they expected. Similarly, the consent capture highlighted that there was a Student Life and Wellbeing team who would be accessing this data; this may have positively informed students of the options available to them. Whilst this finding is promising for the September dataset, the extent to which data collection is possible on a continuous basis is problematic as the mechanism and timing of data capture had a drastic impact on students' participation throughout the year. These difficulties are supported in the literature (e.g. Andrews and Wilding, 2004) where longitudinal surveys reported lower response rates over time which suggests that some drop off is inevitable and expected; however the difference of 69.5%pts between first survey and second survey in this research (81.1% to 11.5%) is significantly greater than in any of the research where a consistent data capture tool was used. It is notable that, when the mental health data was captured via an automated registration task at point of enrolment/ re-enrolment, the opportunity to generate a near population-level baseline was more realistic than it was mid-year when captured via a survey embedded within email communications. Enrolment is mandatory and opening emails is discretionary therefore the difference in responding behaviours is likely attributable, based on the know challenges in the literature, to exposure and awareness of the data collection activity. Students may also perceive the enrolment task to be a more legitimate or official aspect of their experience compared to the email surveys, they may also be more trusting of the security and privacy of the data captured by the Student Record System. Given that a UK student usually only enrols once per academic year, there isn't enough continuality to facilitate timely monitoring of student mental health. Whilst emailing surveys has the ability to be agile, the results show significantly lower participation rates and so don't command the participation required to facilitate operation at large scale. This finding confirms that there is a gap in the standard university digital architecture to monitor population level MHW; commercial platforms, which were reviewed did not appear to support this requirement and therefore universities may need to consider in-house collection and monitoring via other systems which students perceive to be more legitimate than emails such as Student Portals, Virtual Learning Environments and other high traffic university applications e.g. Timetabling apps. Further research in this area is required to highlight the optimal method for capturing MHW data on a continual basis amongst the student population.

It is recognised that longitudinal, continual monitoring facilitates the best opportunity for data 'freshness' (Fritsch, 2008); participants corroborated this stating it was important to have recent data when taking action. September, March and May were specifically chosen to represent key points in the academic year (see 3.3.2.1), however, timing may have impacted response rates as September was pre-teaching whereas both March and May were around assessment. Given that academic factors were highlighted as a risk factor for student MHW, it is important to capture data around these important census points within the calendar. Staff were doubtful that the enrolment data presented a truly accurate picture of students' mental health suggesting that it was probably true in the moment but was inflated based on the positive emotions of starting a new university year and suggested it would swiftly become out of date. Staff also suggested that assessment time would artificially lower the reality of students' wellbeing 'norm'; not only does it impact the scores it may also impact the response rate given the stigma of reporting poor wellbeing or wellbeing decline identified in the literature (see Barriers to identification and disclosure of need and engagement with support2.2.4). The results do corroborate practitioner intuition and evidence significant fluctuations in student mental health between both time points, both at the individual and population level. The proportion of respondents declaring very low wellbeing increased from 3.1% to 20% over the six-month period.

Staff argued that the data needed to be more regularly updated and that a six-month period was too long to be useful for interventions in the interim. This further validates the need to actively confront seasonality when capturing students' mental health data, especially as staff highlighted peaks in service demand around December; infrequent data capture is therefore likely to restrict staff propensity to act on the data which is a serious concern for the validity of the student mental health profiles. As such, a continual method of secure data capture, which achieves both regularity and large-scale participation, beyond just the support seeking students, is required. In such an approach, there is an argument to suggest that, students may become accustomed to sharing their data with the university at routine intervals, which may in turn develop behaviours which influence their propensity for help seeking when they experience changes. Whilst this could be considered a positive outcome that ensures more students access help when they need it, support service staff regard this behaviour as potentially problematic as discussed in *5.2.2.*

Additionally, regarding the WHO-5 itself, awareness was low and experience of utilising nil; perceptions for all interviewees was that it was 'limited' and not as effective as other clinical tools for measuring poor mental health. Given this research has discovered that it has rates of opt-in, when captured systematically at least, and is applicable at all points on the wellbeing spectrum, it is argued that the benefits it offers to all students is worthy of designated training to raise awareness of the WHO-5 amongst university counselling practitioners and therapists. Such training may positively impact adoption and an understanding of how to realise each of the use cases identified in this research.

The representativeness of data capture in this research facilitated a robust exploratory clustering approach. Both hierarchical and partitional clusters were deployed on the September dataset however the partitional clusters had the most distinct overlaps and were therefore the most useful in the profile creation phase where question level responses were used to distinguish otherwise same-score groups e.g. between SP5 and SP6. Most notably, students' reactions to the question 'rested' was a key differentiator and staff found that this would be a useful profile to target existing provision around sleep workshops and therapies to particular student groups in a way which was previously unachievable. Ultimately the WHO-5 is only 5 questions which are themselves highly intercorrelated; as such this limits the clustering power and number of meaningful and distinct clusters which were found in this research. In turn, the profiles that can be generated were limited but did still allow, at the most basic of levels, the service to begin targeting and personalising support at the population level. For example, students in profile SP9 (Positive Wellbeing) may have previously been sent an email promoting services around counselling and mental health. These 7,686 students can now be sent either a different message, potentially less prescriptive and detailed regarding how to seek support and may instead be sent information encouraging their momentum and advising on how to sustain positive thriving mentality at university; they may not even be sent an email at all. The latter scenario in turn allows the university to focus more prescriptive and directive messages to students in, say SP2 "Low Wellbeing" to promote services.

This partially fulfils the requirement of RQ1 to explore how the WHO-5 data can be used to identify distinct university student mental health profiles. The simplistic and basic nature of the WHO-5 profiles validated the need to explore the opportunities afforded by additional datasets to create more specific and nuanced profiles to facilitate personalisation and targeting.

5.1.2. Contextualising mental health data for improved personalisation

The quantitative results of this study reported an average WHO-5 score of 66.3 in September which is 4.3pts higher than was reported by Chow et al. (2018) (which was 15.5 unscaled therefore 62 scaled); however the figures at March and May (42.4 and 47.5 respectively)were both lower than this which evidences the need for research to be explicit about the timing of data capture. This is consistent with some of the warnings in the literature about seasonality (e.g. Ayers et al., 2013). Furthermore, this research reports lower WHO-5 scores correlate to known risk factors such as age, VLE engagement, academic performance and gender. Female students recorded significantly lower levels of wellbeing which is consistent with the literature (Smith, 2016; EQLS, 2016; Thorley, 2017). Furthermore, the EQLS suggested that the gap in WHO-5 scores between male and females in the population is 5 percentage points; this research suggests that the deficit could be even greater amongst university students, with the results of this study reporting a gap of 6.8 percentage points.

During the exploratory analysis phase of the research, additional datasets were assessed in terms of their availability and validity for clustering; the additional datasets which were found to have the greatest potential for clustering based on their clusterability, descriptive trends and availability across the population were: (i) demographic data (age, gender and fee status), (ii) academic achievement and (iii) engagement with digital systems (VLE and CRM). The Hopkins statistic scores were computed for the datasets with continual variables only such as students' age, academic grades, VLE logins, time spent on the VLE and enquiries raised with student support services via CRM; the statistic improved in all cases suggesting there is value in future studies utilising these datasets for clustering. These numerical proxies are, or at least should be, available for the vast majority of students via the SRS, CRM or VLE depending on the local digital architecture, and therefore represent an opportunity for universities to leverage the data they already have within the appropriate ethical and consensual frameworks.

Given there were some relationships between risk and lower scores and there was improvement in the Hopkins statistic, it was expected that combining the datasets would facilitate the generation of more specific clusters with more opportunities for attribute level profiles. The hypothesis here was that more nuanced clusters would generate more nuanced profiles and that these, in turn, would facilitate better segmentation for targeting support and more relevant personalisation. This research has found that including additional contextual information about students and their engagement with university services did not increase the amount of viable clusters within the dataset; in most cases the optimal number of clusters remained at either 2 or 3. This does not necessarily support the hypothesis however it doesn't reject it either as, when analysing the clusters to create the profiles, the research did find that the cluster overlaps decreased as contextual data was added meaning the additional data is useful for creating more distinct student mental health profiles. Remembering that the profiling in the present methodology is not automated, this highlights the extent to which a profiler may interpret and make judgements about the data as an intermediary. This is explored in more detail in 5.2.

Despite the data corroborating the known risk factors around age and gender, these variables were rarely influential in explaining the overlaps for mental health cluster thresholds and therefore few profiles included demographic information. Only 1 profile (SP7) benefited from the inclusion of combined demography (age and gender). Fee status (used to denote whether students are from the UK or Overseas) did not feature either as a discrete cluster or discrete overlap, despite the statistical analysis showing significant differences between subpopulations; this speaks to the limitations of cluster-based profiling for student mental health support which was also found to be applicable to the self-reported datasets.

The self-reported data (whether students felt part of the community and whether they had additional responsibilities such as childcare or employment) were not progressed to the clustering stage as data availability was comparatively low (83.0% and 83.3% compared to an average of 95.4% for the demographic variables) and the Hopkins statistic could not be computed. Despite this, the research found that students who reported 'yes' to feeling part of the university community reported higher rates of wellbeing which is consistent with Tinto's work on the impact that community has on the student experience (1997); despite it not being used in the clustering process in this research, it may still have value for profiling e.g. a targeted campaign to those who reported 'no'. Such a campaign should acknowledge that it can only be implemented to those who shared the data and that students within the 'no' population may be experiencing perfectly healthy levels of wellbeing.

The research found no observable correlation between the WHO-5 and students having additional responsibilities; this is not necessarily surprising given the literature review suggested that these factors are particularly complex and interrelated with several circumstantial variables (see Family, community and lifestyle factors2.2.3.3). Whilst this finding suggests that the data does not lend itself particularly well to a clustering methodology, the data may be useful within other profiling approaches as it is important that the profiles of 'student as parents' and 'student as employees' are not overlooked within the discussion of student mental health. Understanding students' personal experiences is a meaningful and valid means of offering personalised student support, as both the literature review on risk factors and the qualitative results report. Even without the explicit profile label, the research participants identified parenthood and work as potentially underlying factors to the MHW of the only demographic profile identified (SP7- Mature male students reporting low scores for feeling fresh and rested). This suggests that even with additional datasets, cluster-based profiling has its limitations; nevertheless, the outputs do offer a prompt for experienced therapists to interpret cases within the context of the modern student experience which was perceived to be a benefit.

It's important to consider that, whilst the data on community and additional responsibilities was not usable in this research, future quantitative analyses may be able to cater for it if the availability of the data were increased, e.g. if this were a mandatory question within data collection activities, or if the type of data were changed, e.g. from categorical "yes / no" to continual "0-100". Certainly a qualitative approach to creating typologies of "student parents" or "student workers" would give a greater in depth understanding of the challenges faced and the digital proxies available; these data traces are important as without the data to attribute these typologies back to individual students, they could not be incorporated in student-level profiles as the students would not be identifiable and segregable within the population. Practitioners suggested other datasets which were not included in the profiling which would be helpful and would encourage them to approach a student differently; these were based on their own knowledge of risk factors such as sexuality and financial standing (including debt) and whether the student has a registered disability and, additionally, whether the correct support was in place for them (a 'Disabled Student Support Recommendation' (DSSR), in the present setting).

In summary, this research has found that additional contextual data did facilitate the creation of more distinct profiles than WHO-5 data alone but the lack of strong correlative relationships between the contextual variables and the WHO-5 scores across the entire student population meant that utilising risk factors alone are not enough for the whole spectrum of mental health and wellbeing (RQ1). This suggests that future studies looking to replicate a similar approach should seek to include variables related to positive thriving such as the Thriving Quotient (Schreiner, 2010) or PsyCap ("Psychological capital")(Martínez et al., 2019). This research has additionally found that improving the nuance and specificity of student mental health profiles is a process that is more subjective than scientific based on the overlaps often not containing enough statistical distinction to warrant its own cluster. Given these reflections it is pertinent, before moving the discussion to use cases, to first evaluate the cluster-driven methodology in the next section; this offers an opportunity to transparently inform future projects looking to create student mental health profiles.

5.1.3. Clustering data to create profiles: a critique of the methodology

Notwithstanding the requirement to thoroughly and competently design a clustering methodology, the clustering process itself is fairly simple: import data, execute script, export clusters. The subsequent analysis of clusters and overlaps is the profiling stage which attempts to add meaning to the clusters by identifying common attributes within subsets of students. Presently, clustering WHO-5 data over 3 census points did lead to the creation of distinct profiles across both positive and negative wellbeing characteristics; so at a high level the methodology did achieve what it set out to do. The profiles are, in themselves, a contribution of this research and represent the first known attempt to achieve the three V's of big data processing for SMHP: volume, variety and velocity (Gandomi and Haider, 2015). This section discusses the advantages and disadvantages of replicating the approach to creating such profiles in other university settings.

To enable targeted and personalised support, a methodology is required to sort the whole university population into smaller subpopulations and identify homogenous student groups. The methodological decision for choosing clustering was that it is robust in terms of reproducibility, is less susceptible to human error than manual clustering at the scale of the current research and can be computed multiple times consistently with the execution of a script. Although the clustering did take longer for some of the larger September datasets, it did operate well at scale (*'Volume'*) and the R package *cluster,* meant that each student was assigned to a cluster automatically after processing which meant that the profiles, once created, could be applied at both the individual and group level.

With the average processing time being around 4 minutes per dataset, this is indeed faster (*'Velocity'*) than any manual clustering could be on 18,698 observations. However, this research found that, in addition to clustering, there was a requirement to manually analyse the cluster overlaps to create profiles because the additional variables did not increase the number of optimal clusters. There are two findings to note; firstly replicating this research but adjusting the methodology for determining optimal cluster counts would allow the weighting of some indices more than others and may change the outcome of the count in such a way as to create more discrete clusters and therefore less manual profiling through cluster overlap analysis. Based on the subjectivity of the present profile creation, such a change to the methodology may prove useful but would still require human validation. Secondly, as manual profiling rendered the clustering process less automated than a standard cluster analysis, the original desire to achieve student mental health profiles at velocity was not achieved; the human is required to make sense of the overlaps for the profiling process which is time consuming even if the clustering is not. Given that a key recommendation of this research is to create profiles at more frequent intervals this is a key finding and limitation of the current methodology.

In terms of *'Variety'*, it has been concluded that the WHO-5 data does facilitate SMHP however the clustering process as a methodology failed to properly account for the variety of datasets that were on offer e.g. fee status and feeling of community. Without the manual profiling, the contextual data would have been lost in the clusters which, aside from the overlaps, were driven completely by the WHO-5 data; clustering therefore added little value to what is otherwise simply a rules-based approach to filtering the dataset on the aggregated WHO-5 score. For universities choosing to collect WHO-5 data, the WHO-5 profiles identified in this research support the existing body of literature on WHO-5 scores (Ware, 1995; Krieger, 2014; Topp, 2015) and provide enough context to create three or four student mental health profiles at a high level of aggregation e.g.; 'Very Low/ Ham-D Major', 'Low / Ham-D Minor', 'Medium', 'High'. The profiles created in this study add a level of specificity around certain times in the academic year e.g. reducing the threshold for the very low profile from 44 to 24 as the academic year progresses but add little variety to what was already known from the literature. The constraints placed on the data by a clustering methodology (e.g. data availability, and data types such as continual versus ordinal) represent limitations of the clustering approach. Despite this, the fact that the profiler had ultimate control over the data, which never left the organisation's digital environment, may be considered a serious benefit versus digital commercial platforms where profiling occurs within a black box (Hildebrandt and Gutwirth, 2008; Seaver, 2017).

5.2. Profile-based, targeted and personalised Mental Health and Wellbeing support in university settings

The second aim of the research was to explore how University Support Services staff respond to student mental health profiles within the context of their varied roles as mental health and wellbeing professionals. The second section of the chapter discusses the opportunities of SMHP by identifying and discussing the various use cases identified in the research. After their initial presentation, the use cases are examined through the lens of roles and responsibilities to understand the extent to which profiles offer student-level and group opportunities and how these could be integrated as part of a whole university approach to improving student MHW based on the lessons learned from the literature on health promoting universities. Drawing on the literature identified in *2.4.3,* a major consideration within this section is the impact that human/ algorithm data processing has on the agency of staff operating within the student support roles. This represents the third and final contribution arising from this research; the identification of delivery risks which should be considered to address the existing challenges identified in the literature (see 2.2.4 and 2.2.5) and thus maximising the success of profile-based, targeted and personalised mental health support for students.

The challenges of meeting students' needs when disclosure has occurred have been documented in the literature, namely having the resources available to meet demand and deliver appropriate interventions. So regardless of whether profiles *can* be created, the question remains as to how might university student services staff implement profiling as a Whole University approach to targeted and personalised student mental health and wellbeing support? (RQ2). This is the underlying pragmatism within the present research; the profiles may be theoretically sound and algorithmically possible but may be operationally ineffectual when deployed in real CMH teams due to sociocultural factors at play within the working environment. This section therefore explores how, by whom and with what intended purpose the profiles may be utilised in practice. Specifically, 5.2.1 presents the use cases for profiling and is discussed relative to the literature on profiling. 5.2.2 discusses the extent to which roles and responsibilities interact with these use cases and 5.2.3 assesses the impact that profiling activity may have on agency and autonomy within an increasingly platformised he environment. This final section therefore offers universities, policymakers and researchers an opportunity to consider the need for a balance between service delivery and service optimisation with respect to student mental health support.

5.2.1. Potential use cases for student mental health profiling (SMHP)

In the previous section it was asserted that student mental health profiles encompassing both known risk factors and WHO-5 data offer a comprehensive overview of mental health and wellbeing across the student population. This section considers how these profiles may be used for targeted and personalised mental health and wellbeing support.

The qualitative results highlight that staff are open to accessing more data, with those in management having a particular appetite for more data to bring about efficiencies and improvements within the service. This aligns to the literature on equipping university staff with more data (2.2.5) to inform proactive MHW interventions which is part of the enabling activities within the UUK Stepchange for Mentally Health Universities framework (UUK, 2020) which underpins the University Mental Health Charter (Hughes and Spanner, 2019). Despite overwhelming agreement from participants that a targeted and personalised approach to mental health and wellbeing is a better approach, the proactive element of reaching out to students who had not yet asked for help was somewhat inconclusive due to resource constraints and a feeling that this was beyond their remit. This research highlighted that the CMH team were not currently engaged with either targeted or personalised support, despite being equipped with enough data to do so. This suggests that student mental health profiles are not immediately introducible into the current team without risk of low to no adoption, and this may be the case in similar settings across the UK sector. Certainly, it suggests that there is enabling work to do to embed profiling both as theory and a practice and that it should be aligned to a communicated vision for how targeted and personalised support is expected to benefit both students and staff. The remainder of this section aims to give a starting point for improved service design and delivery via offering an exploration of the use cases identified in this research (see 4.4.2).

As Table 13 Overview of use cases identified for student mental health profiles shows, the student mental health profiles are found to have applications across a range of service design and service delivery scenarios; use cases U1-U5 they act as the means to segment the population for taking differential action (Mills, 2022) and for U6-U11 they act as an attribute or comparator group for reporting as is currently deployed in the CMH team on an ad hoc basis for known focus areas e.g. EDI (Equality, Diversity and Inclusion). The use cases presented build on the existing understanding of typical proactive campaigns such as the personalised email approach (U1) and behavioural nudging (U3), which were reviewed in 2.3.2 *Data and technology for targeted and personalised support.* The use cases identified all require staff to utilise or mediate the profiles in a conscious way; notably none of the interviewees suggested that students may see or engage with their profiles in ways that have been adopted in learner analytics approaches (Foster, 2020). Future work may wish to consider how student mental health profiles could be shared with students for institutional transparency, self-awareness and self-regulation.

The academic literature focuses heavily on intervention given the prevalence for research on risk and poor mental health outcomes, however the inclusion of positive profiles in this research encouraged staff to offer prevention scenarios (U3) as well as intervention. This is important given the emphasis throughout policy to take more proactive, early alert style intervention methods (Thorley, 2017; UUK, 2020) despite a lack of published examples in practice. Positive profiles represented a paradox for staff; they were unsure whether action of any kind was appropriate however they suggested motivational campaigns (similar to nudges) to encourage behaviours and learn what is working well by engaging with these students. Staff argued that focus groups and additional surveys were required to understand what strategies those healthy students are employing and feed this back to students in need. The results further corroborate the need outlined in 5.1.2 for the identification of data proxies to nuance the positive profiles.

The data from practitioners highlighted that there is currently a gap in proactively designing any type of interventions which students need, not just those for positive scenarios. The data suggests this, like other approaches in the team, is currently very reactive and relied on reports back from practitioners. Whilst participants did not suggest that the profiles were capable of highlighting all possible interventions required, they did suggest that seeing the characteristics and size of profiles helped to contextualise and prioritise which interventions may need to be designed (U7), offering specific examples such as sleep workshops (mapped to profiles around feeling 'fresh and rested' and burnout for those profiles exhibiting extreme usage of the VLE. This represents an improvement on current practice and validates the utility and validity of considering mental health and wellbeing support through the lens of profiles.

According to university support staff, without the profiles identified in this study, the CMH team would typically advertise services via a 'blanket approach' and rely on students' seeking help. These use cases therefore represent a real opportunity to take a more proactive, evidence-based approach to supporting students' decision-making around the support packages on offer. They suggested however that proactivity across the population may lead to students at low to moderate risk unnecessarily seeking support when they might not have considered or needed it; this was considered both a long term risk in terms of pathologizing the need for support and counteracting students' resilience which the extant literature suggests is important in managing student wellbeing (Chow et al., 2018; Crick, Prickett and Walters, 2021). Given that this study found 63.2% of respondents to all three surveys experienced a significant change in wellbeing at least once in the academic year, the impact of this could be great as it was also considered a short-term risk for exacerbating further the demand for services despite the fact that managers suggested a high rate of re-referral after the first session was already happening now and speculated a lack of data-informed prioritisation as the underlying reason. Noting the risks of students feeling passed on with this onward referral (Zuriff, 2000) there is a need to avoid such situations not just for service efficiencies but to avoid choice 'exteriorisation' as warned by Bradbury et al. (2013). Therefore, U5 – the use of profiles to prioritise and deprioritise students, could mean *not* intervening with those who potentially do not need it (or at least do not need it yet), thus reserving more time, resource and energy for those that do. The potential impact it could have in responding to the challenge of increased disclosure is a real benefit which must however be weighted against the ethical implications of doing so. This is especially poignant as some practitioners struggled with the idea of de-escalation and felt it did not align to their professional ethos or values. Universities considering the use of profiles for risk management should work with specialist service teams to ensure consistency and fairness for the student population and to manage risk with an appropriate level of delegated authority.

Some of the use cases identified (U8 – 11) were applicable for a whole university approach and represent the opportunities from which management staff expected to benefit in their need to plan and resource service effectively. These use cases represent the specificity required to operationalise a whole university approach which has previously been lacking (see 2.1). These use cases do not represent new activities, the data suggests that management particularly already have a focus on the use of data for service design via tools such as the Equality and Diversity dashboard. Such tools are also a core part of the whole university approach to meeting intersectional mental health challenges (Hughes and Spanner, 2019) therefore profiles were seen as an additional piece of information rather than something that would replace what is currently in existence for planning and design the service to meet the diversity of the whole population. Nevertheless, profiles, especially those utilising demography and embracing intersectionality, were seen as an enhancing factor which would improve the quality and specificity with which planning and evaluation can occur. This is crucial as it is a known deterrent for future disclosure if a student has previously had a negative experience (Martin, 2010; Venville, Street and Fossey, 2014); any activity which attempts to deliver the intervention well on first contact is considered valuable.

Returning to the literature review, Tsouros et al. (1998) highlighted three opportunities for a whole university approach; this research argues that the use cases identified for SMHP offer an opportunity to contribute to the first i.e. “1) by protecting the health and promoting the well-being of students, staff and the wider community through their policies and practices” but also “2) by increasingly relating health promotion to teaching and research” (Tsouros, et al., 1998). In the case of the latter opportunity, this research suggests that the inclusion of "support" within the scope is critical to optimising the success of a whole university approach within this definition. Whilst the interviewees discussed and offered data to support the articulation of these use cases, participants also questioned how these use cases may be realised or delivered and by whom.

The next section considers an analysis of the use cases identified for staff use, with respect to the roles within and out with a university CMH team. This is an important factor in the contribution that these use cases may offer as understanding roles and responsibilities and their alignment to specific activities ensures that staff are trained and deployed effectively which was highlighted in the literature as being a key enabler of whole university approaches to mental health (Hughes and Spanner, 2019; UUK, 2020)

5.2.2. Roles and responsibilities for profiling

The literature review explored a wealth of theory and policy which encourage universities to take responsibility for all students' wellbeing, not just those signalling need (see Literature Review – Health Promoting Universities). Participants from the university's CMH team agreed with this notion that the university should serve all students' wellbeing needs and understood some level of prevention was desirable and core to the philosophy of a whole university approach to mental health. Despite this, they suggested that it may not necessarily be the role of the counselling and mental health service alone speculating that academics as well as the wider student services team such as frontline and back-office student support and welfare teams also had a role to play. Failure to appropriately utilise specialist resources and overburden them with general wellbeing tasks is counter-intuitive to SMHP which aims to have a positive impact on student mental health intervention, therefore an understanding of roles and responsibilities is essential.

The CMH team regarded their responsibilities as being aligned to those identified as at risk. For practitioners this was students in the extremely low wellbeing profiles i.e. SP1 (13.4% of the population), MP1 (32.2% of the population) and MayP1

(20.2% of the population). Managers suggested that the PWP role had been designed and introduced to engage with a broader spectrum of wellbeing for both individuals and groups of students. Whilst practitioners acknowledged that the new PWP role was designed to act on a broader spectrum of profiles i.e. not those students with acute issues who required specialist therapies, they still regarded positive mental health profiles out of scope for that role. They did suggest that they considered prevention (U3) to be beneficial to their role to avoid further wellbeing decline, which is aligns to literature calling for early alert and intervention (Thorely, 2017), however they articulated this as students on an already negative trajectory rather than those reporting high WHO-5 scores, regardless of other contextual factors. Given that the positive profiles represent 41.3% of the population in September (13.6% and 20.1% in March and May respectively) this leaves a number of students who may not actually benefit from prevention, without explicit organisational design to deliver it. Furthermore, individuals argued that whilst certain use cases were appropriate to the CMH team they were not necessarily appropriate to their individual role. This finding further confirms the importance of universities considering their organizational structure in relation to expectations or profiling across a broader range of use case.

Considering the mental health practitioner role, these staff engage with students who have specific mental disorders such as eating or bipolar disorders and schizophrenia; similarly counsellors work with students on the acute end of the spectrum with anxiety and depression. They work on agreed caseloads which have specific eligibility criteria for therapy. Practitioners considered personalisation (U1) to be the only viable use case for profiling within their remit and even then were sceptical that profiles would improve the specialist therapy e.g. CBT that they deliver; they were particularly apathetic to the advantages of using profiles around VLE and CRM behaviours if these were not felt to be influential factors by the student. Their suggestion to include data such as disability to enhance usability aligns to the literature on intersectional approaches (King, et al., 2017; Hughes and Spanner, 2019; Lal et al., 2021; Danowitz and Beddoes, 2022; Shobiye, 2022). Nevertheless their feedback was that their approach to triage would remain unchanged and would still rely on their existing tools and use the students' first appointment as the key data gathering exercise. To support the realisation of U1, student mental health profiles using the WHO-5 should be presented as an *additional* instrument at the disposal of a practitioner rather than one which replaces the tools they know and trust e.g. GAD-7 and PHQ-9.

Furthermore, managing risk and prioritising some students over others (U5), was not something which any of the practicing roles within the team felt that they were positioned to deliver. Management staff proposed this use case but notably all practicing staff said that this was not something they would use profiles for currently and therefore this particular use case requires more research. A finding of this research therefore is that universities which seek to use profiles in that way, may need to consider the specific design of a role which identifies risk at the individual level and triage those students into the relevant support system. Notably, this research only engaged with staff from a formal mental health and wellbeing background; there are other roles within university CMH teams who manage appointments and administrate the service; this research did not include those within its scope given they are not working directly with students however this research suggests they may be able to use profiling and future research may wish to investigate whether non-clinical roles may benefit from SMHP.

This was contrary to management's vision for more data upfront to inform therapy decisions to avoid resource drain and suggests a subtle tension between service efficiency and service values which require further exploration. Furthermore, if universities are considering enabling counsellors or mental health practitioners with student mental health profiles they should be aware that the use cases may be limited and any expectations of proactive activity beyond caseload should be made explicit by service designers and managers. This may also include training on how to embed targeted and personalised support within their daily practice.

Use cases U8 to U11 were seen to be associated exclusively with management as part of a programme of service design; as such, profiling should be considered as much as a strategic tool as an operational one. The application of profiling within service planning and evaluation as well as service delivery positions SMHP as a versatile approach that offers universities multiple opportunities for improved design of their

MHW services. However, in addition to these use cases, university leaders are responsible for the successful realisation of use cases U1-U6 through the effective management and support of staff including training and staff development. This may include the promotion and communication of a whole university approach to mental health within the culture of the team. Staff who are expected to act on profiles within their daily service delivery must understand the scope of their role especially where it requires promotion and prevention for all students as well as intervention with those in need. University leaders should communicate not only the benefits of proactivity with the MHW teams but also empower service leaders to make explicit the impact on daily activities which profiling is expected to have e.g. this may involve intervention timelines linked to certain profiles within the student calendar. This leaves teams in no doubt as to how, when and why their activities contribute to personalised and targeted support.

Enabling academic staff to embed wellbeing within the module, programme or faculty environment is an integral part of a functioning Health Promoting University (Tsouros et al., 1998); it was speculated by the MHW team that profiles could be useful to academic roles as some of the profiles draw on VLE and academic performance data. Participants in this study suggested the personal tutoring framework represents an opportunity to use profiles however this, along with other options for integrating wellbeing into academic practice, requires further research, particularly to understand and make clear what the role is for tutors whose ability to contribute to student support strategies may not be as intuitive (Earwaker, 1992). Certainly sharing profiles anonymously without the underlying student data may help to inform pedagogic interventions aimed at improved mental health however sharing student-level profiles with a student's academic has important ethical implications for both the student and staff member. This should not be considered before further research has validated these use cases and identified the necessary enabling actions. Specific training must be considered which should include how and when to refer students for professional help along with setting appropriate boundaries. This should clarify how academic staff would be supported in this to overcome known issues with roles and responsibilities for academic staff undertaking pastoral care (Grant, 2006; Walker, 2018).

Furthermore, the original mechanism for capturing consent only specified that the data would be shared with the student support, CMH team; this may have influenced students' propensity to share their data if they consider these support teams are unlikely to violate the intimacy of their surveillance (Savolainen and Ruckenstein, 2022) i.e. to be a more trusted custodian of their mental health data than academic staff. Conversely there may be even higher rates of opt in if students felt there would be academic as well as wellbeing benefits. This is an opportunity for further study to determine the impact that a wider audience has on student WHO-5 disclosure. All factors considered, the findings do suggest that there are further use cases in other teams for SMHP than have been identified in this research.

5.2.3. Agency and autonomy with respect to student mental health profiling (SMHP)

Whilst this research has found that cluster-based profiling facilitates the segmentation of students into subgroups which mental health teams consider to have multiple positive use cases in university settings, the literature review presented a complex view of algorithms which was present in the data which must be considered. The use of algorithms within society are argued to be interpreted in practice as more than code but part of culture (Seaver, 2017; Bucher, 2018) and there were risks identified both within the literature for algorithmic profiling (see 2.4.3), and the present data. This final section considers the opportunities and challenges of student mental health profiles as per RQ2, *How might university student services staff implement mental health profiling as a Whole University approach to targeted and personalised student mental health and wellbeing support?*

The data in the present study shows that interviewees called out the risk of 'data anomalies' and the cluster algorithm making its own judgements which are consistent with a feeling that there may be accuracy issues within the profiles. The profiling undertaken in this research was a process deployed to make sense of the clustering technique but did involve subjective reasoning. For instance, when analysing overlaps it is apparent to the profiler, where there are multiple possible interpretations and permutations of the data meaning students could be eligible for plural profiles based on their circumstances and the hierarchy with which the profiling rules were applied. For example, a student with a mental health score of 58 could be categorised as MayP5 (Medium Wellbeing: Minimum of a grade 60 and no failed modules) or MayP6 (Medium Wellbeing: No engagement with CRM). This is exciting as it means profiles can be tailored to multiple individual contexts depending on factors impacting their experience and suggests the profiling process is capable of being fluid, flexible and non-deterministic which is consistent with Kreuter et al (2003) who suggest that a methodology for prioritising profiles is required where there are plural possibilities. Where there is more than just algorithmic decision-making taking place and without the full awareness of mental health professionals of the profiling process, this data suggests that a further challenge may be speculation and doubting the legitimacy of the approach. Therefore to improve understanding and thus adoption, such decisions may need to be transparent and presented to stakeholders more forensically than they were in the presentation stage of this study. This would also render mental health and wellbeing professionals active partners during the sense-making process between cluster and profile and less 'docile' as mere recipients of the final output.

In terms of the impact that profiling could have on staff as docile agents, there was no explicit data to suggest that practitioners or managers felt that this was the case although it was not a specific question within the interview design. Certainly, it was acknowledged that some use cases have a greater impact on agency and autonomy than others; use cases which represented indirect actions by management (U6-U11 supporting planning and evaluation) were not considered as problematic in the sense of contradicting professional judgement or having the potential for harm as the use cases which were aimed at direct student level interventions (use cases U1-U5). The results show that practitioners are, in some ways, already creating and using profiles in their current roles for those direct student interventions although these are more akin to typologies rather than profiles as the data and information used to create them are qualitative and gathered in an unstructured way during the first therapy session. Even the initial mental health questionnaire, which could again give data to suggest a high-level profile of mental health, was not always used to personalise the therapy until after the first meeting with the student at which point students were sometimes referred to more relevant services. Some senior members of the team felt this was a wasted opportunity and did not help with ongoing resource constraints on therapy session. The data shows that profiles improved staff perception of the usability of an otherwise large multi-variable dataset; despite the contextual data however the results show that staff feel a profile would never tell the whole student story and would never replace the role of triage by the therapist. As such, this suggests that they themselves would not use profiles to de-escalate (U5), then profiles may not alleviate this pressure without additional resource tasked specifically with profile-based triage.

Staff found it hard to articulate why profiling using additional data on support needs and academic engagement was different to using raw data from the self-referral form suggesting that some of this was natural resistance to change and a preference for their existing tools and approaches for diagnosis and support. It was suggested that profiles may induce a judgement of the student prior to the first therapy session, which was problematic for practitioners (although notably not managers as previously discussed) and not in keeping with standard therapeutic practice. Practitioners seem keen to join the dots between the data themselves rather than having this completed by a profiling process however their discomfort with profiling even as an aid suggests that adoption of profiling amongst this community may be low without the necessary business readiness activities around training and development. To preserve clinical agency but make use of student mental health profiles created via the methodology adopted in this research may require users to develop what Savolainen and Ruckenstein describe as 'novel skills and capabilities to understand and act on algorithmic operations.' (Savolainen and Ruckenstein, 2022); this is consistent with Brown et al. (2022) who specifically highlight the need for technical skills in targeted and personalised student support strategies.

The final element to consider is the level of intimacy between university mental health staff and the algorithms used in the profiling process as this was found to be an avenue for balancing autonomy in relation to algorithmic systems (Savolainen and Ruckenstein, 2022). The defining skillset of university CMH teams is their ability to operate interpersonally within complex human relationships; they are not characterised by a mastery of data analytics and technology. Whilst some MHW workers may have advanced digital skills, this is rarely a requirement of the role and the data in this study found that all were users of quantitative data rather than collectors or manipulators of it. Practitioners did suggest they collected qualitative data during therapy but this was used in relation to the session only. Therefore it is unsurprising that interrogating the outputs of cluster-based profiling was felt to be new and different. A common theme across all interviewees was that they considered the use of student mental health profiles constitutes a fundamentally different approach to their current practice.

Although it was not explicit, it was suggested that such profiles as were created in this study would be something that, in future, somebody else would do for them. As such this creates a distance between them and the underlying algorithm which is a space in which doubt and questions of legitimacy and accuracy can exist. The creation of the present profiles relied on a large student-level dataset and a k-means clustering algorithm, the outputs of which were then interpreted pragmatically by the researcher. The decisions made both in the clustering and profiling processes therefore represent a form of power or control over the team as highlighted in the literature (Bucher, 2018) even though the profiles were created by a human rather than a commercial algorithm or 'black box' (Hildebrandt and Gutwirth, 2008). The reasoning as to why certain factors had been selected for clustering or weighted during profiling were constantly challenged with 'better' proxies suggested stemming from practitioners' own knowledge of risk factors. As such, whilst the clustering algorithm was thoughtfully designed its ability to be considered benign when embedded within the wider activity of targeted and personalised student mental health support was questioned as staff suggested it jarred with their practice.

The data shows specifically that profiles which consider fluctuations in mental health scores are considered to risk pathologizing and overpromoting the need for support in those situations. As such staff regularly asserted that both profiling and targeted and personalised support may not always be the best for the student if they are not already intrinsically motivated to seek help. Similarly, it was suggested that students who have declined in their wellbeing but not sought help should be acknowledged for their resilience rather than encouraged to develop a reliance on the service suggesting their alignment to the feeling of targeted support juxtaposing with choice 'exteriorisation' (Bradbury et al, 2013); thus their hesitations may be likened to the welfarist objections acknowledged by Sunstein (2013). As such, at the policy level, this needs to be considered relative to this use case. Staff did suggest that proactive campaigns could play an important role in planting the seed for help-seeking behaviours and therefore a finding of this research is that the value which profiling adds to targeted and personalised support is communicated via the use cases identified in this research.

The results of this study are consistent with the notion of there being the potential for both acceptance and tension between practitioners and data-driven SMHP. The benefits of the approach are understood but there is a clear need to understand roles and responsibilities in relation to the creation, maintenance and deployment of the profiles as well as an acknowledgement of their limitations and how they may be mapped to levels of support such as Brown's adaptation of the WHO model (Brown, 2018).

The ambiguity of what a future university MHW service looks like for the day-to-day service delivery tasks is understandable; mental health profiling for proactive, pre-emptive support strategies is currently a novel approach which could disrupt the traditional "hit and hope" model. There was a general perception amongst practitioners that data-led profiling or analytics activities of this nature were aligned to roles more senior to them potentially latently equating data with strategy rather than operation. The present research has investigated staff perceptions of SMHP however it was assumed by all participants that these profiles would be generated for them. For universities looking to implement not just profiling, but other forms of proactive, population-level support, there is a lot of localised vision setting and training to first take place before academic and professional teams may work together with a broader scope. Universities may need to consider the introduction of roles specifically tasked with population level engagement; roles with hybrid skillsets specifically tasked with student outreach. A service design approach should balance the needs of students to develop resilience and self-serving behaviours with the need to offer specialist support when professional practitioners deem it necessary. As the scope of profile users and use cases increases so too does the level of sensitivity and risk of data privacy invasion. Given the need to ensure that access to personally identifiable data is legitimate and restricted through General data Protection Regulations (GDPR), an important consideration for universities when implementing profiling is to conduct a privacy impact assessment. This ensures that even though the systems and datapoints are not being made available, the profiles, when attributed back to individuals, do not breach the access agreed with the student (i.e. the data subject). It also ensures that humans remain present and active within the algorithmic fabric of the profiles and exercise final judgement on the creation of new meaning from the data.

6. Conclusions

6.1. Summary and significance of the research

In UK universities at present, there are increasing rates of mental health disclosure amongst student populations at the macro-level which obscure, at the micro-level, differential rates of help-seeking behaviour and support adoption. Furthermore, there are documented challenges to meeting the needs of *all* students based on resource constraints. This thesis is an academic reaction to both the problem and the UK HE sector's call for more data-led intervention and prevention techniques to improve student mental health outcomes. The current research supports a workstream on data analytics within an OfS funded project aiming to "identify actionable insights [and] to deliver holistic approaches to student health, wellbeing and education" (Northumbria University Press Release, 2019).

The aim of this thesis was to inform how university student services teams may use student-level data for the improved design and delivery of targeted and personalised mental health and wellbeing support packages for the whole student body. It has demonstrated that WHO-5 data can be used to create profiles at various points within the academic year, and for all students on a spectrum of positive to negative states of mental health. It has also evidenced that the specificity and usability of these profiles are further improved by the addition of data from other aspects of the student experience although there is much scope to explore this further. This was achieved by collecting mental health data and applying a clustering to profiling methodology which created small homogenous groups from an otherwise large heterogenous student population.

Whilst the clustering method to transform raw data into profiles has been found to be suboptimal with respect to the volume and variety of clusters generated, it nevertheless supported the delivery of several research outputs. One of these outputs are in the form of 28 profiles which, along with the overarching methodological approach, were presented to staff working within a student CMH team. A second output is the eleven use cases for the use of student mental health profiles which were identified by staff. These use cases included targeted and personalised support thus clearly satisfying the original research questions on the opportunities for SMHP.

This research provides substantial quantitative and qualitative evidence that not only is it a technically viable approach but also that it has a good breadth of use cases for both direct and indirect mental health service interventions. The impact that this research makes is twofold as there are implications for the operational provision of university services as well as at least two academic research fields: (i) student mental health and wellbeing and (ii) the digitalisation of health and the human experience.

Operationally, Universities may leverage their own data to identify the profiles identified within this research or may adopt, at least, adapt the methodology and learn how to create their own profiles. The use cases offer policymakers in university settings and managers within University Support Services an opportunity to review their current practice and may represent the business case for the investment in new services. Furthermore, sector bodies may review the use cases identified and consider how best to support institutions in delivering these consistently and within a measurable framework. The uses cases confirm that Whole University approaches to student mental health require services which span a wider scope of roles and responsibilities beyond the traditional student services remit meaning Universities wanting to implement data-led mental health strategies should consider these findings carefully.

From an academic perspective, the results and findings here contribute new knowledge regarding the impact of SMHP on the agency and autonomy of university staff which is a previously unexamined topic in HE studies on student mental health. The thesis asserts that this is a viable approach for improving the design and delivery of the support that universities offer to students but that certain risks relating to algorithmic profiling e.g. a perception of data errors and anomalies are present in SMHP too. Encouragingly, whilst counternarratives on algorithms and platforms in HE assert that there is a risk to student and staff agency (Pasquale, 2016), this research additionally found no evidence that SMHP would have a *negative* impact on the role of practitioners although certain questions remain outstanding such as 'who would create these profiles in practice?', 'who is best placed to carry out each of these use cases?' and 'what skills and training does each role require to be successful?'.

6.2. Contribution to knowledge, policy and practice

This thesis has made three contributions to new knowledge which combine to offer a viable, evidence-based approach to services tasked with delivering mentally healthier student populations. This is important given there is little academic research documenting how sector level policy promoting proactive data and technology solutions, has been translated into effective institutional practice. As such the profiles identified in this research represent the first contribution of this thesis. Unlike the hypothesised 'student subsets' (Harrer et al., 2019) discussed in the literature, these profiles are reflective of the UK student experience and can either be utilised in settings where the required data is already being captured, or act as aspirational targets for institutions who are in the process of evaluating their data requirements.

Building on the current research for profiling students (Xu, Wang, and Su, 2002; El Ansari et al., 2011; Li et al, 2017; Broglia, 2021), the critically reflective discussion of the data and methodology presented in this thesis represents the second contribution of the thesis- an original approach to profiling student mental health in university settings. The research validates existing literature which suggests that the WHO-5 is a useful tool for screening population level student mental health (Downs et al., 2013; Downs et al., 2015). It has done so with a sample size greater than many other studies in this field (e.g. Tija, Givens and Shea, 2005; Andrews and Wilding, 2004) which tend to focus on collecting data via clinical tools and therefore are inherently concerned with a smaller subset of students exhibiting poor mental health issues. Additionally, this thesis also finds that frequency of capture is important to practitioner buy-in, which has been speculated but not confirmed until now, and documents the benefits and limitations of cluster-based profiling which is now available to inform the research design and decision-making process of future SMHP initiatives.

Finally, an appraisal of the opportunities, challenges and benefits that SMPH may offer to Universities is presented in a set of critically evaluated use cases which expand on the originally hypothesised scope of targeted and personalised support, and represent the thesis' final contribution. The literature evidences that preventative and proactive mental health interventions which draw on aspects of education (Durlak, 1997), communication (Breet et al., 2021) and digital strategies (Lattie et al., 2019) are of particular importance to the future of personalised student wellbeing support (de Vibe et al. 2013, El-Den et al., 2020; Richards and Tangney, 2008). Expanding on the documented success of such interventions, the findings of the present research further assert that profiling offers staff and services an opportunity to target and personalise such interventions, as well as embedding profiles within the assessment and evaluation of interventions, resulting in a uniquely bespoke and sophisticated programme of support.

As a result of these contributions to theory and practice it is now possible to understand the role profiling can play in designing and delivering better student mental health and wellbeing services within university settings. This can inform university investment strategies relating to IT infrastructure such as the need to fund additional methods of mental health data collection and analysis. It may also influence the design and resourcing of support services so that they have the tools available to them to act on data driven profiles. Finally it should influence the definition of roles and responsibilities within the University's organisational structure so to ensure that staff have the right skillsets and are given appropriate training to deliver mental health and wellbeing support to varying degrees for all students.

6.3. Recommendations for future research

Based on the results shown in this thesis, several key areas are viable for future academic enquiry which will continue to ensure that this approach may be ethically and effectively implemented in university settings.

Firstly, whilst this research captured data for 81.1% of students at enrolment, further research is required to understand students' motivations for doing so (and indeed not doing so) and their expectations for subsequent activities by the university. This will provide insight into students' qualitative perceptions of student mental health analytics and may in influence our understanding of why the data capture was notably lower at the second and third census points. Further research into what can be expected as a 'norm' response rate for such activity would allow universities to contextualise their response rate and evaluate whether investment in survey promotion would be beneficial. Furthermore, whilst there will inevitably be students who will abstain from data collection activities, the extent to which this is hindered by fear, stigma or other reasons would allow more investigation into consent models to ensure that students have the opportunity to opt in with more information. Although from a technical perspective 81.1% was adequate for the current research to gain statistically significant analysis, maximising the response rate in practice will improve the extent to which universities can use the data to intervene and reduce the number of students who remain silent and in need of support. This will further our understanding of response rates and continual data monitoring from an ethical perspective including how to design support for students who wish to remain anonymous.

Secondly, whilst the strength of this study lies in the originality of its methodology, findings and contributions, inspiring a range of UK universities to adopt similar strategies requires acknowledgement of the limitations of the clustering methodology and recommendations for continual methodological improvements. The research found that the risk factors did not enhance the quality or specificity of mental health profiles at the positive end of the wellbeing spectrum. Therefore understanding risk more qualitatively and exploring positive mental health factors empirically will enhance our ability to identify and/or develop alternative data proxies for analytics-based approaches in future. Given the finding that cluster-based profiling placed constraints on otherwise valuable datasets, future research may also wish to consider other methodologies for reaching the same output of meaningful student mental health profiles. This may include an evaluation of commercial algorithms, which have been proven to predict outcomes with a high degree of accuracy, and which may also facilitate profiling for student mental health support. This improves on the current clustering methodology and specifically the decision to use the algorithmic majority rule for identifying optimal number of clusters (see 3.3.3.1) rather than specifying the desired number of clusters. As the optimal number of clusters remained mostly unchanged even with additional data around risk, this meant that certain attributes were underutilised during the profiling process because of limited nuance within the clusters. Given the plethora of datasets available in the current study, coupled with the recommendation for more proxies for positive engagement going forward, this limitation should be addressed in future research designs via alternative clustering or partitioning methods. Such inquiry may also seek to better utilise datasets which this study found to be unsuited to cluster-driven profiling (e.g. data on additional responsibilities such as childcare), to assess whether there is still scope to target and personalise MHW support for students based on this information. This is important to ensure that we continue to translate known risk factors into effective strategies for support this reducing the deficit discourse on why students' mental health deteriorates and instead place more emphasis on how universities can be better position to support.

Additionally, the present research considered only one university which already has comparatively advanced digital architecture (evidenced by award-winning collaborations with world leading technology partners such as Microsoft) and a streamlined organisational structure based on a service redesign within the last decade. The university is also well engaged with the Office for Students on the Student Mental Health Competition call and therefore many of the themes for proactive support are already embedded within university culture which may have influenced the proclivity for staff to highlight these as use cases. Staff at other universities may not be as exposed to this type of strategy and it should also be noted that, with the increase in private providers in the sector, there is a growth in outsourced mental health provision which would further complicate and limit the immediate applicability of this research in those settings. It has also been identified that the use cases may go beyond the remit of professional staff charged with intervention and therapy; as such future research should consider the utility of profiles within other contexts including within academic and faculty teams to validate and potentially expand on the list of use cases identified herein. Universities already operate different strategies to the provision of student services represented by different organisational structures, teams and investment levels.

Finally, as this thesis represents the evaluation of the theoretical opportunities for targeted and personalised support via SMHP, future studies should look to implement the approach in multiple settings to test its hypotheses. This should include the design of an evaluation framework which considers the known challenges around disclosure and self-referral and provide evidence as to whether profile-based support improves engagement with university services over and above standard approaches. This may also seek to explore the extent to which asking students to take the WHO-5 survey is itself an impactful intervention by taking a baseline of self-referrals to the CMH team at enrolment without data capture and subsequently comparing them to the same point the following year with data capture thus ascertaining whether the survey itself prompts students to seek help and disclose.

It is crucial to note that this study did not engage with students on their perceptions of student mental health analytics or the profiles and profiling methodology. Engaging students in the process of sensemaking with respect to the profiles and methodology for profiling as contributed by this research is an obvious and necessary next step in the journey towards implementing student mental health profiles in service design. Whilst this research has contributed much to our foundational understanding of what is possible with regards to SMHP, along with the use cases and staff feedback, this should be adequately addressed within all the recommendations for further research listed above.

6.4. Concluding remarks

This thesis has articulated that data driven student mental health profiling offers rich opportunities to addressing the increasing demand on university pastoral services. Universities with a vision to innovate their mental health and wellbeing services may learn from this research and capitalise on the opportunity to (i) identify which students need support in the population, (ii) assess the level of urgency and (iii) venture an initial level of personalisation to their specific needs. Such approaches only work in certain conditions such as when students share their data and when staff understand and trust the approach enough to act upon it so inviting staff and students to contribute to a shared vision for a mentally healthier university enabled by technology should be prioritised by leaders and service designers.

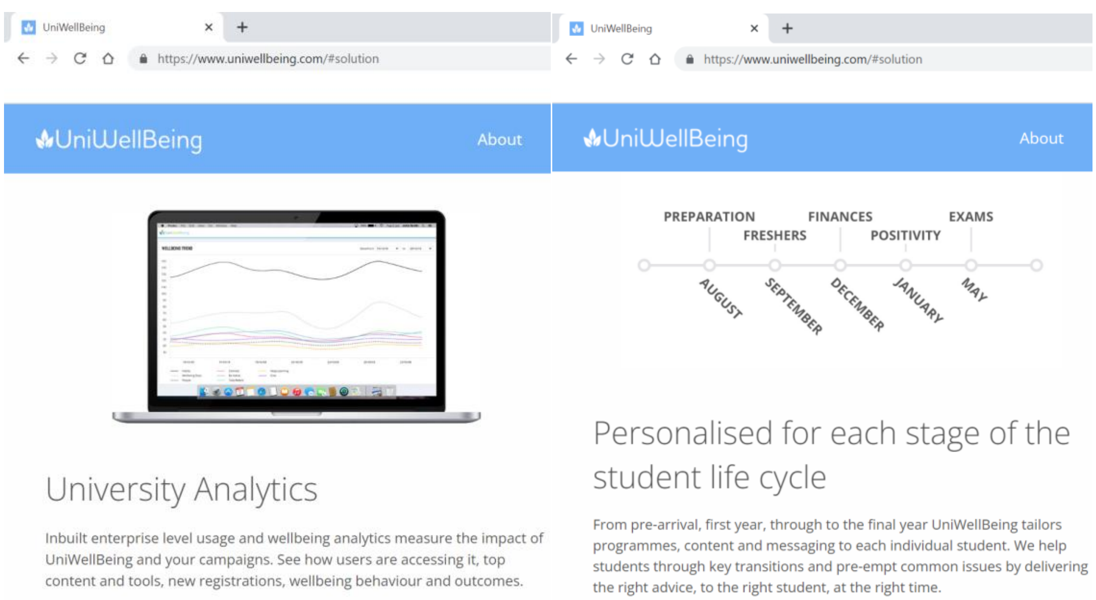
Appendices

Appendix 1: Literature Review

Appendix 1a: Examples of commercial Platforms to support student mental health and wellbeing
Appendix 1b: Results of Systematic Search for Mental Health Clustering Approaches

Appendix 1a: Examples of commercial Platforms to support student mental health and wellbeing

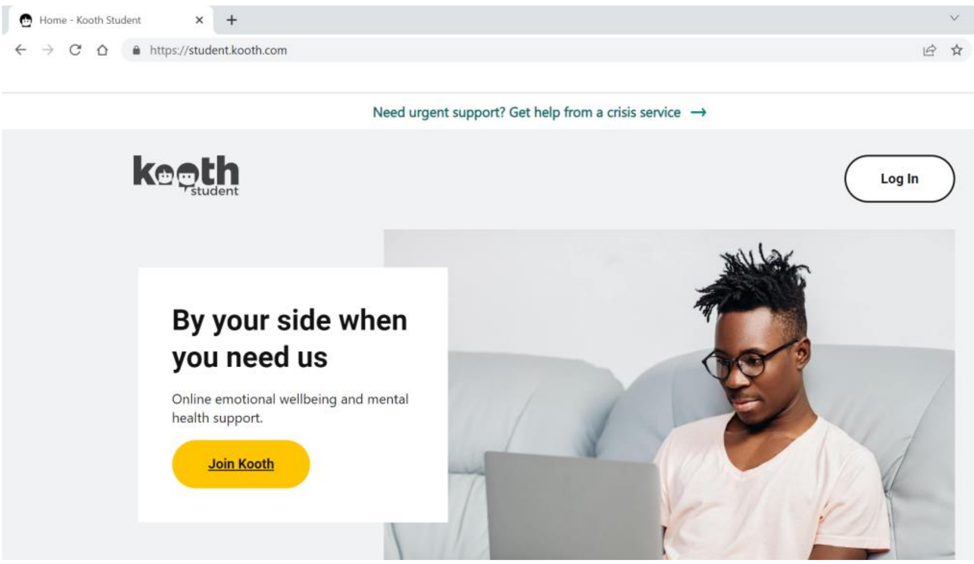
UniWellBeing offer a digital software product which they suggest “makes building healthy habits and looking after wellbeing fun, stimulating and interactive.”[14] . Figures on their website suggest over 1,000,000 students at 75 universities worldwide; this size would suggest the tool aims for university-wide adoption and is not aimed just at those in diagnosed need. In addition to early intervention and preventative support, which is language echoing the recommendations of Thorley’s 2017 paper, the tool boasts a wellbeing analytics function and refers to personalisation.



Appendix Figure 1 UniWellBeing webpage, https://www.uniwellbeing.com/#solution, accessed on 29/5/22 showing the Wellbeing Analytics functionality and referencing personalisation

[14] website homepage, https://www.uniwellbeing.com, accessed 29/05/2022

Another solution is Kooth which offers digital counselling and limited data services to universities to allow monitoring of the population. However it appears from screenshots of the platform that it is aimed at students already seeking support[15] and therefore not positioned for a whole university approach which seeks to address the barriers to students seeking help.



Appendix Figure 2 Kooth Students homepage as accessed on 29th May 2022 showing the text "By your side when you need us"

Togetherall, although not a platform specific to HE, is deployed at some large UK institutions and, like Kooth, offers a digital platform for student mental health support. Unlike Kooth, Togetherall is aimed at all students; "This allows people who might otherwise slip through the cracks to seek preventative help and go on to seek other support."[16]. Togetherall purports to collect some data using some of the clinical tools identified in 2.2.2 but the extent to which this data is then shared at the student level with universities is unclear.

[15] When consulting the Kooth Students website, the tagline is "By your side when you need us" which suggests it is for those in need rather than for the wider population. Website: https://student.kooth.com

[16] https://togetherall.com/en-gb/mental-health-services/students/, accessed 29/05/22

Appendix 1b: Results of Systematic Search for Mental Health Clustering Approaches

Appendix Table 1 Results of literature database review for mental health clustering and profiling

Article Title	Author	Publication Year	Summary
Exploring temporal behaviour of app users completing ecological momentary assessments using mental health scales and mood logs	Bond et al.	2019	Clustering is used in this approach to understand how new and expectant mothers engage with a screening tool for pre and post-natal depression. The HILDA workflow is applied which is a framework specifically designed for managing interaction data in health settings (Mulvenna et al, 2018). N = 1461; app users C = 4 (unnamed but descriptions provided on usage behaviour) T = 1; clusters are static points in time
A cluster analysis of basic personality inventory (BPI) adolescent profiles	Bonynge, E.	1994	Applying a two-stage clustering procedure similar to Starks et al., the basic personality inventory (BPI) scale is used to derive psychopathological profiles before making comparisons between male and female adolescents. N = 213; adolescents C = 4 (Mental Health Maladjustment, Interpersonal Maladjustment, High-Risk Rebellion, and Adjustment) T = 1; clusters are static points in time
The prediction of disruptive behaviour disorders in an urban community sample: the contribution of person-centred analyses.	Burt et al.	2004	A study comparing the advantages and disadvantages of a varied- centred analysis to person-centred analysis in the assessment of childhood behaviour trends. Burt et al argue that the two approaches are complementary in supporting targeted interventions. N = 164; mother/child pairs C = 4 ('AVG', 'COGPROBS', 'PSYPROBS', 'COGSTIM'; these labels are described as 'heuristic tools' (p. 1166) T = 3; at pregnancy, four and eleven years old
A multi-faceted approach to characterizing user behaviour and experience in a digital mental health intervention	Chen et al.	2019	The study uses data collected from various digital mental health apps. Clustering is used to categorise users' based on their style of engagement with the platforms. N = 98; app users C = 4 (Low Usage, High Usage, Daily Feats Users, Day to Day Users) T = 1; clusters are static points in time (after the eight week research period)

Appendix Table 1 continued….

Article Title	Author	Publication Year	Summary
Insights into Antidepressant Prescribing Using Open Health Data	Cleland et al.	2018	The study uses open access datasets, rather than personally identifiable data, to test the hypothesis that antidepressant usage and economic deprivation are conflated by the level of depression in a confined population. The elbow method (Thorndike,1953) was used to determine the volume of clusters at each stage of analysis N = not stated; GP practices C = 2, 3 and 4 (variations of 'deprived' and 'non-deprived' practices but actual clusters are not named at each stage) T = 1; clusters are static points in time
Numbing and Dysphoria Symptoms of Posttraumatic Stress Disorder among Iraq and Afghanistan War Veterans: A Review of Findings and Implications for Treatment	Hassija, Jakupcak, and Gray	2012	Hassija et al. critically review empirical literature to evaluate the current models of mental health outcomes for veterans of the conflict in Iraq and Afghanistan. By gathering the research on three and four cluster approaches they can consolidate the evidence and make suggestions for treatment. N = N/A clusters not derived in research C = N/A clusters not derived in research T = N/A clusters not derived in research
Peer Victimization and Mental Health Outcomes for Lesbian, Gay, Bisexual, and Heterosexual Youth: A Latent Class Analysis	Heiden-Rootes, et al.	2004	The study uses a type of cluster analysis known as Latent Class Analysis (LCA) to identify victimization profiles amongst young high school students, Data was then used to draw comparisons with the LGBQ characteristic and mental health outcomes. N = 15,624; high school students C = 3 ('Minimal', 'Bullying' and 'Physical and Sexual Violence') T = 1; clusters are static points in time
Common Patterns of Service Use in Children's Mental Health.	Lambert et al.		Lambert et al. document clearly the clustering approach that they used to find patterns of mental health care amongst children. They use discriminant analyses to understand the characteristics of each pattern which aids labelling the clusters and subsequent replication of results with random subsamples for validity and replicability. This study created a cluster of 'atypical' children from outliers (a 2% trim of the main dataset) plus a comparatively small cluster. N = 979; children C = 6 ('Brief outpatient', 'Extended outpatient', 'Hospital + outpatient', 'Non-residential MT0', 'Extended residential', 'Atypical outliers') T = 1; clusters are static points in time

Appendix Table 1 continued….

Article Title	**Author**	**Publication Year**	**Summary**
Families Matter: Social Support and Mental Health Trajectories Among Lesbian, Gay, Bisexual, and Transgender Youth.	McConnell, Birkett and Mustanski	2016	Similar to Heiden-Rootes et al. McConnell, Birkett and Mustanski investigate the relationship between support for LGBT youths, victimisation and mental health outcomes. Unlike the other studies in this systematic review, McConnell et al. used clusters identified in previously published research. N = N/A clusters not derived in research C = 3 ('Low support', 'Nonfamily support', 'High support'- clusters not derived by McConnell et al.) T = N/A clusters not derived in research
The problem of "just for fun": Patterns of use situations among active club drug users.	Starks et al.	2010	Starks et al. adopt a two-stage exploratory clustering procedure on a dataset of club drug users; the clusters were used to predict substance dependence. N = 400; club drug users C = 3 ('Situationally Restricted', 'Pleasure Driven', 'Situationally Broad') T = 2; results were after replicated 12 months
Predictive Big Data Analytics using the UK Biobank Data	Zhou et al.	2019	Using two methods of unsupervised clustering (K- means and Ward's hierarchal clustering) on multisource healthcare data, the study compares N = 9,914 (7,931 training data and 1,983 test data) C = 2 ('1','2') T = 1; clusters are static points in time

Appendix 2: Methodology

Appendix 2a: Data Availability Schedule
Appendix 2b: Adams' Applicability Checklist (1994)
Appendix 2c: Interview Questions
Appendix 2d: R Packages Used in Clustering
Appendix 2e: Biography
Appendix 2f: Extracts from research journal

Appendix 2a: Supplementary data availability at each census point

Data	Enrolment	March	May
Gender (Male, Female, Non Binary)	Y	Y	Y
Age (as a continual numerical variable)	Y	Y	Y
Student having additional responsibilities - Self reported	Y	Y	Y
Student feeling part of the community - Self reported	Y	Y	Y
Fee status – UK student, EU student or International student	Y	Y	Y
Previous academic performance – grade from 0-100	Y- Continuing students only	Y- Semester 1	Y- Semester 2
Previous academic performance – count of failed modules			
Engagement with the Virtual Learning Environment – count of access	N		
Engagement with the Virtual Learning Environment – duration of access in hours	N		
CRM data – count of enquiries raised	N		

Appendix 2b: Mapping of current research to Adams' applicability checklist (1994)

Situations where semi structured interviews may be considered	**The Current Research**
If you need to ask probing, open-ended questions and want to know the independent thoughts of each individual in a group	This is applicable to the investigation of Student Mental Health Profiling as the thoughts of the individual may impact their own propensity to use this as part of their existing, professional approach for mental health support
If you need to ask probing, open-ended questions on topics that your respondents might not be candid about if sitting with peers in a focus group	Not applicable in the sense that there were no focus groups conducted however as the participants are part of the same team with varying levels of authority, it was required to create an ethical environment where they could be candid about their approach without fear of retribution
If you need to conduct a formative program evaluation and want one-on-one interviews with key program managers, staff, and front-line service providers	This research is not a formative evaluation.
If you are examining uncharted territory with unknown but potential momentous issues and your interviewers need maximum latitude to spot useful leads and pursue them	This research does represent unchartered territory as SMHP is not currently used to target and personalise mental health support at Northumbria University.

Appendix 2c: Semi-structured Interview questions

Q1: Can you briefly explain your role?

The purpose of this question was to understand job titles and whether the participant was engaged directly or indirectly with students and what type of therapy and student support they specialised in.

Q2: Do you use data or analytics to target or personalise mental health support in your role currently?

The purpose of this question is to continue exploring the roles and responsibilities of the participant and their existing knowledge and practice of data driven MHW support. The question invites an understanding of how well utilised data is, how it is being used currently and whether this may differ by role. It also opens conversation for whether data is perceived as a legitimate tool for university mental health services. This question aims to uncover how various stakeholders perceive targeted mental health support and compare it with their current approach; this will help to contextualise the as is state of support and the size and scope of change required to operationalise SMHP.

Q3: During the presentation I presented several student mental health profiles which have emerged through a clustering and analysis process. How valid and valuable are these profiles to you in your role?

The purpose of this question, which was asked when the profiles were presented on the screen, is to take a deep dive into the profiles and understand which ones resonate with the participants and illicit reflections on where they may see opportunities or challenges for using these profiles to take proactive action. This is an open section of the interview process where the interviewee can go at their own pace and either systematically work through each profile or highlight profiles which are particularly noteworthy and discuss or ask further questions. Conversational prompts were used to raise themes of student privacy, participant understanding, concerns and opportunities to make the profiles better.

Q4: Has the presentation of the student mental health profiles made you think differently about your approach or Northumbria's approach to student mental health?

This question aims to explore the scope for changes in intervention design and evaluation, team structures and resources, and what, of anything, they would do differently having seen the profiles. It also aims to explore other approaches which may be better placed to achieve the aims of targeted and personalised support compared to SMHP.

Q5: Of all the things we've discussed today, what would you say is the most important thing to consider regarding Student Mental Health Analytics for a Whole University Approach to Student Mental Health?

This final question allows the participant to summarise their reflections and highlight any reflections which have been prominent themes in the discussion. It will be useful to understand and gauge the general sentiment towards the profiles and the SMHP approach and the main concerns. It is also a chance for the participant to review anything that has been discussed and amend or reaffirm their position.

Appendix 2d: R packages used in cluster analyses

The following packages were used in the cluster analyses;

- base; a standard package containing the basic functions required to perform statistical analyses in RStudio such as reading csv files, performing descriptive analyses e.g. mean and range and printing charts to pdf format. The standard deviation across the five questions was also computed to see how consistently students scored.
- stats; used in this study is to perform agglomerative hierarchical clustering using the 'hclust', divisive hierarchical clustering using 'hcut' and partitional clustering 'kmeans' functions. The average linking method was selected in all three approaches to ensure comparability; although it requires more computation than the major alternative, the single linkage approach, it is deemed to outperform it and create more stable clusters (Seifoddini, 1989;

Li and Rijke, 2017). It is also used to compute a cophenetic matrix and cophenetic correlation to understand the amount of distortion introduced in to the dataset by the hierarchical clustering process (Sokal and Rohlf, 1962)

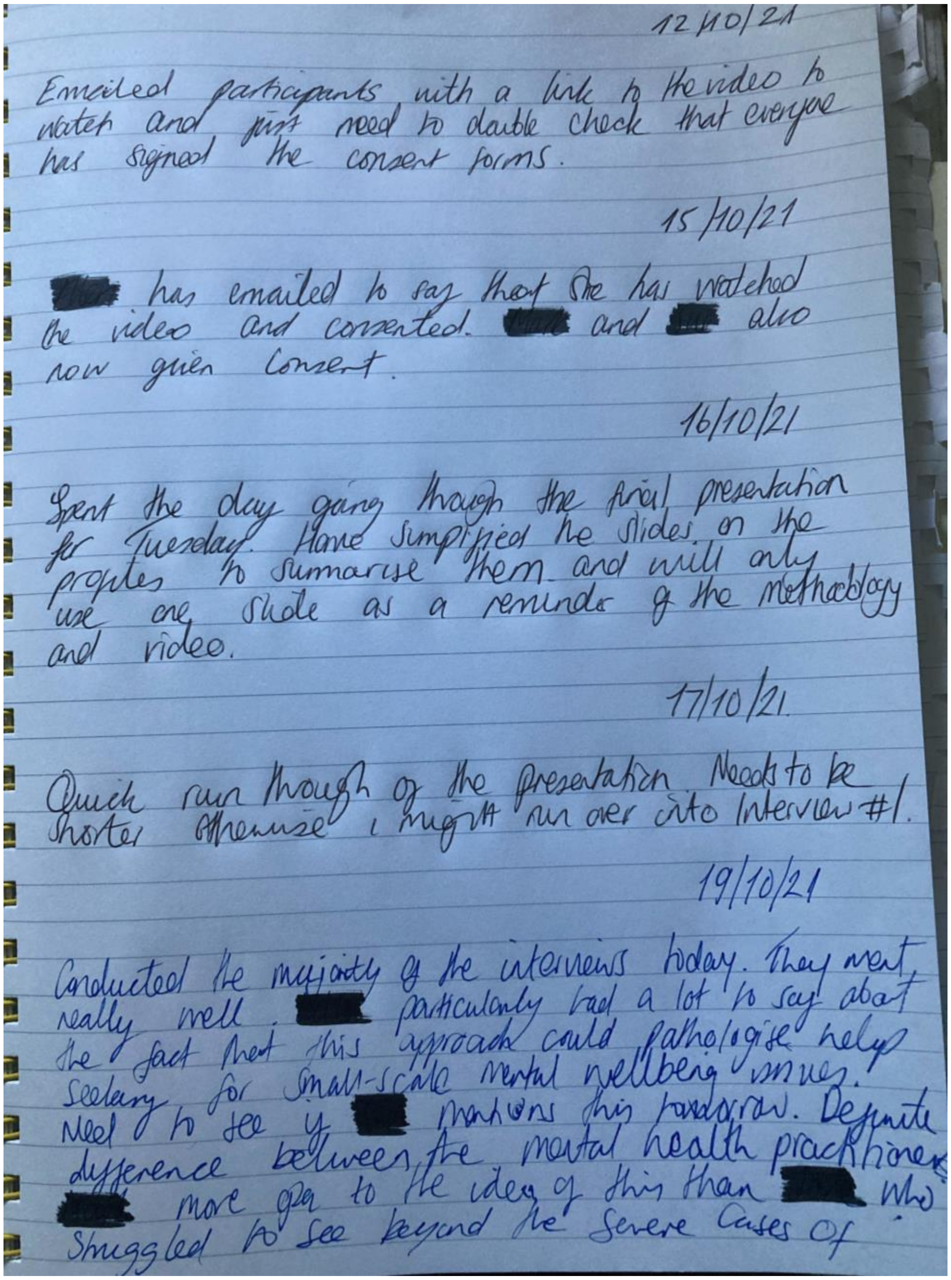
- factoextra; used to calculate a Hopkins statistic (Hopkins, 1954) which is the method used in this study to measure cluster tendency. Hopkins statistics facilitate commentary on which datasets may produce profiles more suited to targeted or personalised interventions. Measuring cluster tendency is important as it can, early in the analysis, suggest whether clustering is a viable analysis technique or whether other approaches should be considered (Jain and Dubes, 1988). This package is also used to generate dendrograms from the cluster outputs of the 'hclust', 'diana' and 'kmeans' processes via the 'fviz_dend' and 'fviz_cluster' functions.
- cluster; used to execute the 'daisy' function which computes dissimilarity, a key aspect of cluster analysis. Specifically, 'daisy' facilitates the 'gower' method which is used throughout the analysis for non-numeric data e.g. wellbeing labels versus wellbeing scores
- NBClust; used to evaluate the optimal number of clusters
- Ggplot2 and cowplot; graphical packages used for advanced charting of statistical outputs to illustrate cluster distribution

Appendix 2e: Mini Biography

I am a PhD researcher at Lancaster University- in the context of this research this is my overriding perspective. I am also a Head of Student Success at Arden University, responsible for, amongst other things, the appropriate resourcing of a student welfare and wellbeing department. Before that I spent two years as an Assistant Director for Student Engagement at Northumbria University, where the current research takes place. I managed the service through Covid-19, lockdowns and challenges; during this time I saw first-hand the impact that this was having on students' mental health but also on staff wellbeing too. I believe that the OfS project has the potential to find new ways of supporting students using data and technology but that we must understand the risks with this.

I utilise data daily and am conscious that my career has developed because of my ability to "tell powerful stories" with data (as was once told to me by a previous line manager) and identify solutions to problems based on these data. I have a strong affinity with digital approaches and am more digitally literate than many people; having grown up in the late 1990s in a middle-class environment I had access to a computer and the internet from an early age and was encouraged to embrace information technology at school as this was seen to be the 'future'.

Appendix 2f: Research Journal



12/10/21

Emailed participants with a link to the video to watch and just need to double check that everyone has signed the consent forms.

15/10/21

[redacted] has emailed to say that she has watched the video and consented. [redacted] and [redacted] also now given consent.

16/10/21

Spent the day going through the final presentation for Tuesday. Have simplified the slides on the profiles to summarise them and will only use one slide as a reminder of the methodology and video.

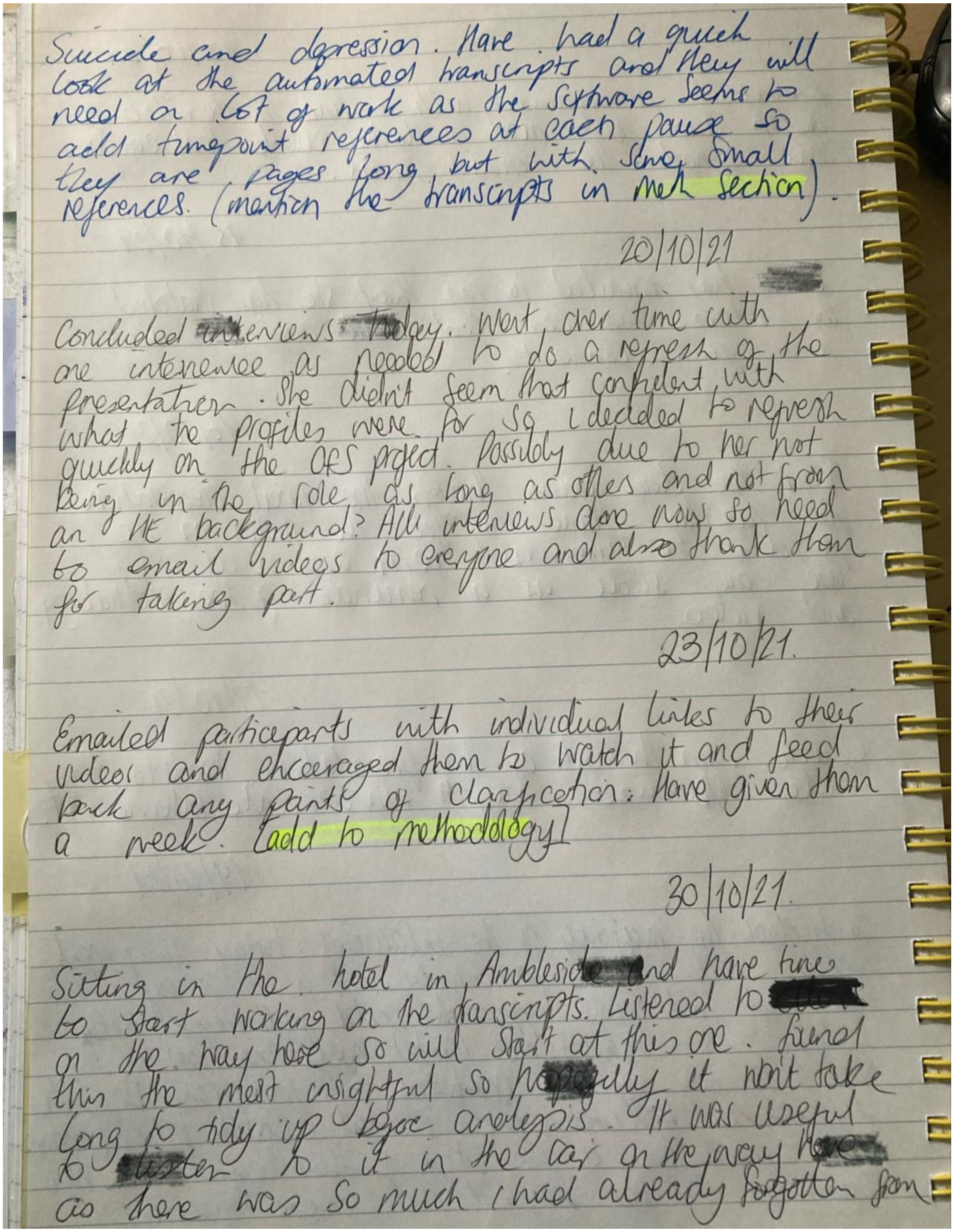
17/10/21

Quick run through of the presentation. Needs to be shorter otherwise i might run over into Interview #1.

19/10/21

Conducted the majority of the interviews today. They went really well. [redacted] particularly had a lot to say about the fact that this approach could pathologise help seeking for small-scale mental wellbeing issues. Need to see if [redacted] mentions this tomorrow. Definite difference between the mental health practitioners [redacted] more open to the idea of this than [redacted] who struggled to see beyond the severe cases of

Figure 19 Research Journal Extract


Suicide and depression. Have had a quick look at the automated transcripts and they will need a lot of work as the software seems to add timepoint references at each pause so they are pages long but with some small references. (mention the transcripts in meth section).

20/10/21

[redacted]

Concluded interviews today. Went over time with one interviewee as needed to do a refresh of the presentation. She didn't seem that confident with what the profiles were for so I decided to refresh quickly on the OfS project. Possibly due to her not being in the role as long as others and not from an HE background? All interviews done now so need to email videos to everyone and also thank them for taking part.

23/10/21.

Emailed participants with individual links to their videos and encouraged them to watch it and feed back any points of clarification. Have given them a week. [add to methodology]

30/10/21.

Sitting in the hotel in Ambleside and have time to start working on the transcripts. Listened to [redacted] on the way here so will start at this one. Found this the most insightful so hopefully it won't take long to tidy up before analysis. It was useful to [redacted] listen to it in the car on the way here as there was so much I had already forgotten from

Figure 20 Further extract of research journal

Appendix 3: Descriptive Analyses

Appendix 3a: WHO-5 Data Analysis

Seasonality

Appendix Table 2 Average score by question and aggregated WHO-5 score

Survey tranche	1. I have felt cheerful and in good spirits	2. I have felt calm and relaxed	3. I have felt active and vigorous	4. I woke up feeling fresh and rested	5. My daily life has been filled with things that interest me	Average of aggregated WHO-5 score
September 2020	3.5	3.3	3.2	3.1	3.4	66.3
March 2021	2.4	2.1	2.0	1.9	2.2	42.4
May 2021	2.6	2.3	2.3	2.1	2.5	47.5

Appendix Table 3 Aggregated WHO-5 scores by high level wellbeing grouping

MHW Label	**Count and population proportion of respondents**					
	September 2020		March 2021		May 2021	
HAM-D/Major Depression (WHO-5 Scores less than 20 inclusive)	569	3.1%	749	20.0%	560	16.1%
HAM-D/Minor Depression (WHO-5 Scores between 24 and 32 inclusive)	879	4.7%	738	19.7%	526	15.1%

Low Wellbeing (WHO-5 Scores between 36 and 48 inclusive)	2361	12.7%	958	25.6%	838	24.0%
OK (WHO-5 Scores more than 52 inclusive)	14,789	79.5%	1,296	34.6%	1,562	44.8%

Appendix Table 4 Changes in wellbeing for respondents to all three surveys

WHO-5 Score	*Respondents*
Consistently OK Wellbeing (scores greater than 50)	28.0% (n= 252)
Consistently Low Wellbeing (scores of 32,36,40,44 or 48)	2.7% (n= 24)
Consistently with the range for Ham-D/ Minor (scores of 24,26 or 28)	1.4% (n= 13)
Consistently with the range for Ham-D/ Major (scores less than 22)	4.2% (n= 38)
Significant Fluctuation (more than 10% change across label boundaries)	63.2% (n= 568)
Minor Fluctuation (within 10% change across label boundaries)	0.4% (n= 4)

Appendix Table 5 Changes by question from the September survey to the March survey

Over the last two weeks:	*At no time*	*Some of the time*	*Less than half of the time*	*More than half of the time*	*Most of the time*	*All the time*
1. I have felt cheerful and in good spirits	0.5% to 3.2%	6% to 23.9%	8.6% to 26.9%	23.1% to 23.5%	48.5% to 18.2%	13.3% to 3.2%
2. I have felt calm and relaxed	1.3% to 9.4%	8.1% to 26.8%	12.9% to 26.7%	24.8% to 19.5%	41.3% to 14.8%	11.5% to 2.8%
3. I have felt active and vigorous	2.1% to 12.1%	8.4% to 25.9%	15.6% to 27.5%	25.4% to 19%	36.4% to 13%	12.1% to 2.6%
4. I woke up feeling fresh and rested	4.1% to 19%	10.4% to 24.8%	16.2% to 24.5%	24.4% to 15%	33.1% to 13.5%	11.8% to 3.2%
5. My daily life has been filled with things that interest me	1% to 7.9%	7.9% to 28.6%	10.8% to 22.8%	23.2% to 20.2%	41% to 16%	16.2% to 4.5%

Appendix Table 6 change in population distribution by score including p values and chi-squared statistic (df = 1)

WHO-5 Score	September to March		March to May	
0	0.1% to 1.1%	p = 1.00, χ2 =93.1	1.1% to 0.6%	p = 0.01, χ2 =4.8
4	0.2% to 1.8%	p = 1.00, χ2 =187.6	1.8% to 1.3%	p = 0.04, χ2 =2.6
8	0.2% to 2.6%	p = 1.00, χ2 =280.6	2.6% to 2.4%	p = 0.28, χ2 =0.3
12	0.5% to 3.1%	p = 1.00, χ2 =207.5	3.1% to 3%	p = 0.44, χ2 =0
16	0.7% to 5.2%	p = 1.00, χ2 =427	5.2% to 3.7%	p = 0.00, χ2 =8.3
20	1.3% to 6.4%	p = 1.00, χ2 =375.4	6.4% to 5.1%	p = 0.01, χ2 =5
24	1.2% to 6.2%	p = 1.00, χ2 =383.1	6.2% to 4.1%	p = 0.00, χ2 =16.1
28	1.5% to 5.9%	p = 1.00, χ2 =272.5	5.9% to 5.1%	p = 0.07, χ2 =2.1
32	2% to 7.6%	p = 1.00, χ2 =341.5	7.6% to 5.9%	p = 0.00, χ2 =8.2
36	2.3% to 6.5%	p = 1.00, χ2 =180.1	6.5% to 5.8%	p = 0.11, χ2 =1.4
40	3.3% to 6.6%	p = 1.00, χ2 =94.1	6.6% to 6.8%	p = 0.59, χ2 =0
44	3.3% to 7.2%	p = 1.00, χ2 =121.2	7.2% to 5.8%	p = 0.01, χ2 =5.8
48	3.8% to 5.3%	p = 1.00, χ2 =19.1	5.3% to 5.7%	p = 0.78, χ2 =0.5
52	4.5% to 5.3%	p = 0.99, χ2 =4.7	5.3% to 5.5%	p = 0.66, χ2 =0.1
56	5.1% to 4.5%	p = 0.07, χ2 =2.2	4.5% to 5.6%	p = 0.98, χ2 =4.1
60	6.4% to 3.8%	p = 0.00, χ2 =39	3.8% to 5.1%	p = 1.00, χ2 =7.3
64	6.3% to 3.5%	p = 0.00, χ2 =42.7	3.5% to 4.1%	p = 0.91, χ2 =1.6
68	7.4% to 4%	p = 0.00, χ2 =56.8	4% to 4.3%	p = 0.79, χ2 =0.6
72	8.5% to 3.3%	p = 0.00, χ2 =117.5	3.3% to 4.9%	p = 1.00, χ2 =10.8
76	8.8% to 2.9%	p = 0.00, χ2 =148.1	2.9% to 4.2%	p = 1.00, χ2 =7.9
80	14.1% to 2.9%	p = 0.00, χ2 =366	2.9% to 4.4%	p = 1.00, χ2 =11.3
84	5.4% to 1.6%	p = 0.00, χ2 =99.8	1.6% to 2.2%	p = 0.98, χ2 =4.2
88	3.3% to 1%	p = 0.00, χ2 =61.2	1% to 1.5%	p = 0.98, χ2 =3.8
92	2.5% to 0.7%	p = 0.00, χ2 =48.6	0.7% to 0.9%	p = 0.83, χ2 =0.6
96	1.6% to 0.4%	p = 0.00, χ2 =31.7	0.4% to 0.6%	p = 0.94, χ2 =1.9
100	5.6% to 0.9%	p = 0.00, χ2 =150.7	0.9% to 1.5%	p = 0.99, χ2 =4.8

Question level analysis

Appendix Table 7 September 2020 survey results by question and answer

Over the last two weeks:	*At no time*	*Some of the time*	*Less than half of the time*	*More than half of the time*	*Most of the time*	*All the time*	*Average score*
1. I have felt cheerful and in good spirits	0.5% (n= 86)	6% (n= 1107)	8.6% (n= 1602)	23.1% (n= 4297)	48.5% (n= 9026)	13.3% (n= 2480)	3.53
2. I have felt calm and relaxed	1.3% (n= 246)	8.1% (n= 1505)	12.9% (n= 2403)	24.8% (n= 4619)	41.3% (n= 7685)	11.5% (n= 2140)	3.31
3. I have felt active and vigorous	2.1% (n= 385)	8.4% (n= 1565)	15.6% (n= 2896)	25.4% (n= 4733)	36.4% (n= 6764)	12.1% (n= 2255)	3.22
4. I woke up feeling fresh and rested	4.1% (n= 760)	10.4% (n= 1935)	16.2% (n= 3006)	24.4% (n= 4530)	33.1% (n= 6165)	11.8% (n= 2202)	3.08
5. My daily life has been filled with things that interest me	1% (n= 180)	7.9% (n= 1470)	10.8% (n= 2000)	23.2% (n= 4319)	41% (n= 7625)	16.2% (n= 3004)	3.44

Appendix Table 8 March 2021 survey results by question and answer

Over the last two weeks:	*At no time*	*Some of the time*	*Less than half of the time*	*More than half of the time*	*Most of the time*	*All the time*	*Average score*
1. I have felt cheerful and in good spirits	4.4% (n= 164)	23.9% (n= 893)	26.9% (n= 1006)	23.5% (n= 878)	18.2% (n= 680)	3.2% (n= 120)	2.37
2. I have felt calm and relaxed	9.4% (n= 353)	26.8% (n= 1003)	26.7% (n= 997)	19.5% (n= 729)	14.8% (n= 553)	2.8% (n= 106)	2.12
3. I have felt active and vigorous	12.1% (n= 452)	25.9% (n= 969)	27.5% (n= 1029)	19% (n= 710)	13% (n= 485)	2.6% (n= 96)	2.03
4. I woke up feeling fresh and rested	19.0% (n= 712)	24.8% (n= 927)	24.5% (n= 915)	15% (n= 561)	13.5% (n= 506)	3.2% (n= 120)	1.89
5. My daily life has been filled with things that interest me	7.9% (n= 297)	28.6% (n= 1070)	22.8% (n= 854)	20.2% (n= 755)	16% (n= 597)	4.5% (n= 168)	2.21

Appendix Table 9 May 2021 survey results by question and answer

Over the last two weeks:	*At no time*	*Some of the time*	*Less than half of the time*	*More than half of the time*	*Most of the time*	*All the time*	*Average score*
1. I have felt cheerful and in good spirits	3.0% (n= 106)	20.3% (n= 708)	23.3% (n= 811)	24.4% (n= 850)	24.3% (n= 847)	4.7% (n= 164)	2.61
2. I have felt calm and relaxed	9.1% (n= 318)	22.5% (n= 785)	25.4% (n= 885)	21.1% (n= 734)	18.3% (n= 637)	3.6% (n= 127)	2.28
3. I have felt active and vigorous	9.3% (n= 325)	20.0% (n= 696)	25.9% (n= 902)	21.7% (n= 756)	19.0% (n= 662)	4.2% (n= 145)	2.34
4. I woke up feeling fresh and rested	15.0% (n= 524)	21.8% (n= 760)	23.4% (n= 815)	19.6% (n= 683)	15.3% (n= 535)	4.8% (n= 169)	2.13
5. My daily life has been filled with things that interest me	5.3% (n= 185)	22.1% (n= 772)	21.3% (n= 741)	24.0% (n= 835)	20.8% (n= 725)	6.5% (n= 228)	2.52

Appendix Table 10 Standard deviation by question and aggregated WHO-5 score

Survey tranche	1. I have felt cheerful and in good spirits	2. I have felt calm and relaxed	3. I have felt active and vigorous	4. I woke up feeling fresh and rested	5. My daily life has been filled with things that interest me	Average of aggregated WHO-5 score
September 2020	1.0	1.2	1.2	1.3	1.2	20.1
March 2021	1.2	1.3	1.3	1.4	1.3	22.2
May 2021	1.3	1.3	1.3	1.4	1.3	23.1

Appendix Table 11 Correlation matrices by question for each survey

September	*Q1*	*Q2*	*Q3*	*Q4*	*Q5*
Q1	1.00				
Q2	0.75	1.00			
Q3	0.68	0.63	1.00		
Q4	0.67	0.65	0.68	1.00	
Q5	0.67	0.60	0.64	0.63	1.00

March	*Q1*	*Q2*	*Q3*	*Q4*	*Q5*
Q1	1.00				
Q2	0.73	1.00			
Q3	0.67	0.60	1.00		
Q4	0.65	0.65	0.66	1.00	
Q5	0.66	0.58	0.60	0.61	1.00

May	*Q1*	*Q2*	*Q3*	*Q4*	*Q5*
Q1	1.00				
Q2	0.75	1.00			
Q3	0.71	0.65	1.00		
Q4	0.68	0.69	0.68	1.00	
Q5	0.69	0.63	0.64	0.64	1.00

Appendix 3b: Results by demographic attributes

September

Appendix Table 12 WHO-5 score groupings by gender (September)

WHO-5 Score	Female N = 10,147	Male N = 8,330	Other N = 13	Data not available N = 108
0 – 20	3.8%	2.1%	15.4%	3.7%
24- 32	5.8%	3.5%	7.7%	4.6%
36-48	14.9%	9.9%	53.8%	13.0%
52-100	75.5%	84.5%	23.1%	78.7%

Appendix Table 13 Aggregated WHO-5 scores by gender in September

WHO-5 Score	Female N = 10,147		Male N = 8,330		Other N = 13		Data not available N = 108	
0	0.1%	3.8%	0.1%	2.1%	0.0%	15.4%	0.0%	3.7%
4	0.2%		0.1%		0.0%		0.0%	
8	0.3%		0.1%		0.0%		0.9%	
12	0.7%		0.3%		7.7%		0.0%	
16	0.9%		0.5%		0.0%		0.0%	
20	1.6%		0.9%		7.7%		2.8%	
24	1.4%	5.8%	1.0%	3.5%	7.7%	7.7%	1.9%	4.6%
28	1.8%		1.2%		0.0%		0.9%	
32	2.6%		1.2%		0.0%		1.9%	
36	2.8%	14.9%	1.8%	9.9%	7.7%	53.8%	1.9%	13.0%
40	3.8%		2.7%		15.4%		4.6%	
44	4.0%		2.5%		23.1%		4.6%	
48	4.4%		3.0%		7.7%		1.9%	
52	5.1%	75.5%	3.7%	84.5%	0.0%	23.1%	5.6%	78.7%
56	5.6%		4.5%		0.0%		6.5%	
60	6.7%		6.1%		0.0%		5.6%	
64	6.6%		5.9%		0.0%		7.4%	
68	7.8%		6.9%		15.4%		7.4%	
72	8.7%		8.3%		7.7%		7.4%	
76	8.5%		9.1%		0.0%		10.2%	
80	13.2%		15.2%		0.0%		20.4%	
84	4.8%		6.1%		0.0%		2.8%	
88	2.6%		4.3%		0.0%		0.9%	
92	1.7%		3.5%		0.0%		0.9%	
96	1.0%		2.2%		0.0%		0.9%	
100	3.1%		8.7%		0.0%		2.8%	

Appendix Table 14 Aggregated WHO-5 scores by age in September

WHO-5 Score	Late Teens N = 2,322		20-29 N = 11,724		30-39 N = 1,650		40-49 N = 800		50-59 N = 281		Data not available N = 1821	
0	0.0%	2.2%	0.2%	3.3%	0.1%	2.8%	0.0%	3.0%	0.0%	2.5%	0.0%	3.1%
4	0.1%		0.1%		0.2%		0.3%		0.0%		0.3%	
8	0.2%		0.3%		0.2%		0.1%		0.0%		0.1%	
12	0.4%		0.7%		0.3%		0.3%		0.4%		0.3%	
16	0.5%		0.8%		0.4%		0.4%		1.1%		0.9%	
20	1.0%		1.3%		1.6%		2.0%		1.1%		1.4%	
24	1.0%	3.9%	1.3%	5.2%	0.9%	3.5%	0.9%	2.8%	0.4%	2.8%	1.6%	5.3%
28	1.2%		1.7%		1.2%		1.0%		1.8%		1.2%	
32	1.7%		2.1%		1.5%		0.9%		0.7%		2.5%	
36	1.6%	12.4%	2.7%	13.4%	1.4%	9.9%	1.9%	9.3%	1.8%	8.9%	2.2%	12.9%
40	2.8%		3.5%		2.9%		2.4%		1.8%		3.1%	
44	3.6%		3.3%		3.3%		2.0%		2.1%		3.7%	
48	4.4%		3.9%		2.4%		3.0%		3.2%		3.9%	
52	5.0%	81.5%	4.6%	78.1%	3.5%	83.8%	3.8%	85.0%	6.0%	85.8%	4.1%	78.8%
56	6.0%		5.3%		3.8%		4.9%		3.9%		4.1%	
60	7.5%		6.5%		5.9%		6.0%		4.3%		5.9%	
64	7.6%		6.3%		6.6%		3.8%		4.6%		5.6%	
68	9.1%		7.1%		6.9%		6.4%		5.7%		7.7%	
72	9.2%		8.2%		8.7%		10.4%		8.9%		8.6%	
76	10.5%		8.2%		9.3%		11.6%		11.4%		8.5%	
80	12.9%		13.0%		17.5%		19.1%		19.2%		17.4%	
84	5.1%		5.1%		6.4%		7.1%		6.0%		5.8%	
88	2.5%		3.4%		3.7%		3.3%		5.3%		3.6%	
92	2.1%		2.6%		3.2%		2.6%		3.2%		1.6%	
96	0.9%		1.6%		2.4%		1.6%		2.1%		1.1%	
100	3.0%		6.3%		6.0%		4.5%		5.0%		4.9%	

Appendix Table 15 Aggregated WHO-5 scores by fee status in September

WHO-5 Score	Home N = 14,059		Overseas N = 3,895		Data not available N = 644	
0	0.1%	3.4%	0.2%	1.4%	0.0%	5.1%
4	0.2%		0.1%		0.8%	
8	0.2%		0.2%		0.2%	
12	0.7%		0.1%		0.2%	
16	0.8%		0.2%		1.7%	
20	1.4%		0.7%		2.3%	
24	1.4%	5.3%	0.6%	2.1%	2.2%	7.6%
28	1.7%		0.7%		1.7%	
32	2.2%		0.8%		3.7%	
36	2.7%	14.3%	1.1%	6.2%	3.0%	16.5%
40	3.6%		1.8%		5.1%	
44	3.8%		1.5%		4.7%	
48	4.3%		1.9%		3.7%	
52	5.0%	76.9%	2.2%	90.2%	5.6%	70.8%
56	5.8%		2.8%		3.3%	
60	7.0%		4.4%		5.6%	
64	7.0%		3.9%		5.1%	
68	7.8%		5.8%		7.1%	
72	8.9%		7.3%		6.8%	
76	9.1%		7.9%		7.3%	
80	13.5%		16.2%		15.4%	
84	4.7%		7.8%		4.8%	
88	2.5%		6.6%		3.0%	
92	1.5%		6.3%		1.6%	
96	0.9%		4.1%		1.2%	
100	3.1%		14.9%		4.0%	

Appendix 3c: Results on students' additional responsibilities

September

Appendix Table 16 Aggregated WHO-5 scores by self-reported feeling of being part of the university community in September

WHO-5 Score	Yes N = 11,947		No N = 3,481		Data not available N = 3,170	
0	0.1%	7.4%	0.3%	1.9%	0.2%	2.6%
4	0.1%		0.4%		0.2%	
8	0.1%		0.7%		0.1%	
12	0.4%		1.3%		0.2%	
16	0.4%		1.6%		0.8%	
20	0.8%		3.1%		1.2%	
24	0.9%	9.6%	2.2%	3.4%	1.4%	4.6%
28	1.1%		3.3%		1.2%	
32	1.4%		4.0%		2.0%	
36	1.9%	20.6 %	4.2%	10.7 %	1.9%	11.5%
40	2.6%		5.9%		3.0%	
44	3.0%		4.7%		3.2%	
48	3.2%		5.8%		3.5%	
52	4.0%	62.4 %	6.4%	84.0 %	3.9%	81.3%
56	4.6%		7.1%		4.9%	
60	6.2%		7.6%		5.9%	
64	6.5%		6.0%		5.7%	
68	7.6%		6.9%		7.1%	
72	9.1%		6.9%		8.3%	
76	9.6%		6.4%		8.1%	
80	15.2 %		8.0%		16.8 %	
84	5.9%		2.6%		6.4%	
88	3.7%		1.2%		4.2%	
92	3.0%		0.7%		2.7%	
96	1.9%		0.6%		1.3%	
100	6.7%		1.8%		5.7%	

Appendix Table 17 Aggregated WHO-5 scores by students declaring additional responsibilities in September

WHO-5 Score	Yes N = 11,676		No N = 3,815		Data not available N = 3,107	
0	0.1%	3.2%	0.2%	3.1%	0.2%	2.6%
4	0.1%		0.2%		0.2%	
8	0.3%		0.1%		0.1%	
12	0.6%		0.5%		0.2%	
16	0.7%		0.9%		0.7%	
20	1.3%		1.3%		1.2%	
24	1.2%	4.5%	1.1%	4.9%	1.4%	4.4%
28	1.6%		1.7%		1.2%	
32	2.1%		1.8%		1.9%	
36	2.5%	12.5 %	2.3%	13.1 %	1.9%	11.6%
40	3.4%		3.1%		2.9%	
44	3.3%		3.3%		3.3%	
48	3.8%		3.8%		3.5%	
52	4.6%	79.7 %	4.4%	78.9 %	4.0%	81.4%
56	5.2%		5.2%		4.7%	
60	6.6%		6.6%		5.7%	
64	6.6%		5.7%		5.7%	
68	7.4%		7.5%		7.2%	
72	8.6%		8.4%		8.4%	
76	8.8%		9.2%		8.1%	
80	13.7 %		13.2 %		16.9 %	
84	5.3%		4.8%		6.3%	
88	2.9%		3.8%		4.3%	
92	2.3%		2.9%		2.7%	
96	1.6%		1.6%		1.4%	
100	5.3%		6.3%		6.0%	

Appendix 3d: Results by VLE Engagement

March

Appendix Table 18 Aggregated WHO-5 scores by the total count of students' Virtual Learning Environment login events between September and March

WHO-5 Score	0-99 logins N = 2,128		100-199 logins N = 1,117		More than 200 logins N = 496	
0	1.1%	19.9%	1.3%	20.9%	0.4%	18.3%
4	1.9%		1.8%		1.4%	
8	2.2%		3.5%		2.0%	
12	3.2%		2.9%		3.0%	
16	5.5%		4.8%		4.4%	
20	6.0%		6.7%		7.1%	
24	5.4%	18.1%	7.5%	23.1%	6.9%	19.2%
28	5.9%		6.5%		4.8%	
32	6.8%		9.0%		7.5%	
36	6.5%	24.6%	6.2%	26.5%	6.9%	27.8%
40	6.2%		7.8%		5.8%	
44	7.2%		6.2%		9.5%	
48	4.7%		6.4%		5.6%	
52	5.1%	37.4%	5.4%	29.5%	6.0%	34.7%
56	4.7%		4.4%		3.8%	
60	3.4%		4.2%		4.2%	
64	3.9%		2.6%		3.8%	
68	3.9%		3.9%		4.4%	
72	3.4%		3.0%		3.8%	
76	3.3%		2.1%		3.0%	
80	3.7%		1.9%		1.8%	
84	2.0%		0.7%		1.6%	
88	1.3%		0.4%		0.6%	
92	0.9%		0.3%		0.4%	
96	0.5%		0.2%		0.4%	
100	1.3%		0.3%		0.6%	

Appendix Table 19 Aggregated WHO-5 scores by students' average Virtual Learning Environment login events per module attempted between September and March

WHO-5 Score	0-49 logins N = 2,547		50-99 logins N = 1,028		More than 100 logins N = 166	
0	1.4%	20.5%	0.4%	19.5%	0.6%	16.3%
4	1.9%		1.8%		0.6%	
8	2.4%		3.0%		1.8%	
12	3.2%		2.7%		3.0%	
16	5.3%		5.1%		3.6%	
20	6.3%		6.5%		6.6%	
24	5.7%	18.9%	7.8%	22.2%	4.2%	17.5%
28	5.9%		6.0%		5.4%	
32	7.2%		8.4%		7.8%	
36	6.7%	24.9%	6.0%	26.9%	5.4%	27.7%
40	6.3%		7.5%		6.0%	
44	6.9%		7.3%		10.2%	
48	4.9%		6.1%		6.0%	
52	4.7%	35.7%	6.7%	31.4%	6.0%	38.6%
56	4.5%		4.7%		4.2%	
60	3.5%		4.3%		4.2%	
64	3.7%		3.3%		2.4%	
68	3.8%		4.2%		4.2%	
72	3.2%		3.3%		6.0%	
76	3.0%		2.3%		4.8%	
80	3.7%		1.3%		1.2%	
84	1.8%		0.9%		1.8%	
88	1.3%		0.1%		1.8%	
92	0.9%		0.0%		1.2%	
96	0.5%		0.2%		0.0%	
100	1.2%		0.2%		0.6%	

Appendix Table 20 Aggregated WHO-5 scores by the total hours spent on the Virtual Learning Environment per student between September and March

WHO-5 Score	0-99 hours N = 2,959		100-199 hours N = 589		More than 200 hours N = 193	
0	1.2%	20.6%	0.7%	19.0%	0.0%	13.5%
4	1.8%		2.2%		1.0%	
8	2.7%		2.7%		0.5%	
12	3.2%		2.7%		2.1%	
16	5.4%		3.9%		4.7%	
20	6.4%		6.8%		5.2%	
24	6.1%	19.3%	7.0%	21.7%	6.2%	20.7%
28	6.0%		5.6%		5.2%	
32	7.1%		9.2%		9.3%	
36	6.6%	25.1%	5.8%	26.1%	7.3%	31.1%
40	6.7%		6.3%		6.7%	
44	7.0%		7.0%		####	
48	4.9%		7.1%		5.7%	
52	4.9%	34.9%	6.8%	33.1%	6.7%	34.7%
56	4.6%		4.4%		4.1%	
60	3.8%		3.4%		4.7%	
64	3.3%		4.6%		3.1%	
68	3.7%		4.4%		6.2%	
72	3.3%		3.6%		3.1%	
76	2.9%		3.1%		2.6%	
80	3.3%		1.4%		1.0%	
84	1.7%		1.0%		0.5%	
88	1.1%		0.3%		0.5%	
92	0.8%		0.0%		1.0%	
96	0.4%		0.2%		0.5%	
100	1.1%		0.0%		0.5%	

Appendix Table 21 Aggregated WHO-5 scores by the average amount of hours spent on the Virtual Learning Environment per student between September and March (per module attempted)

WHO-5 Score	0-49 hours N = 3,246		50-99 hours N = 419		More than 100 hours N = 76	
0	1.2%	20.6%	0.5%	17.2%	0.0%	11.8%
4	1.8%		1.7%		1.3%	
8	2.7%		1.9%		0.0%	
12	3.3%		1.7%		2.6%	
16	5.3%		4.3%		3.9%	
20	6.3%		7.2%		3.9%	
24	6.1%	19.7%	7.6%	19.6%	2.6%	19.7%
28	6.1%		4.5%		5.3%	
32	7.5%		7.4%		####	
36	6.5%	25.1%	6.4%	28.9%	6.6%	30.3%
40	6.7%		6.2%		6.6%	
44	6.7%		9.5%		####	
48	5.2%		6.7%		3.9%	
52	4.9%	34.6%	7.4%	34.4%	9.2%	38.2%
56	4.5%		5.0%		3.9%	
60	3.7%		4.3%		3.9%	
64	3.6%		2.9%		2.6%	
68	3.9%		4.5%		5.3%	
72	3.3%		3.1%		7.9%	
76	2.9%		3.6%		1.3%	
80	3.2%		1.0%		1.3%	
84	1.6%		1.2%		0.0%	
88	1.0%		0.7%		0.0%	
92	0.7%		0.2%		1.3%	
96	0.4%		0.2%		1.3%	
100	1.0%		0.2%		0.0%	

Appendix Table 22 correlation coefficients for March VLE variables and WHO-5 Questions

Over the last two weeks:	*Total count of logins*	*Average logins per modules attempted*	*Total hours spent*	*Average hours spent per module attempted*
1. I have felt cheerful and in good spirits	-0.08	-0.08	-0.05	-0.05
2. I have felt calm and relaxed	-0.08	-0.11	-0.07	-0.09
3. I have felt active and vigorous	-0.07	-0.09	-0.05	-0.05
4. I woke up feeling fresh and rested	-0.08	-0.09	-0.06	-0.06
5. My daily life has been filled with things that interest me	-0.04	-0.05	-0.04	-0.04

May

Appendix Table 23 Aggregated WHO-5 scores by the total count of students' Virtual Learning Environment login events between March and May

WHO-5 Score	0-99 logins N = 574		100-199 logins N = 985		More than 200 logins N = 496	
0	0.7%	16.7%	0.5%	17.4%	0.6%	15.2%
4	1.2%		1.6%		1.1%	
8	2.1%		2.2%		2.5%	
12	3.1%		3.5%		2.8%	
16	4.5%		4.1%		3.3%	
20	5.1%		5.5%		4.9%	
24	4.2%	13.4%	5.0%	15.7%	3.6%	15.3%
28	3.7%		4.8%		5.8%	
32	5.6%		6.0%		5.9%	
36	5.6%	21.6%	5.1%	24.0%	6.2%	24.8%
40	5.7%		7.3%		6.8%	
44	5.7%		6.1%		5.6%	
48	4.5%		5.5%		6.2%	
52	5.4%	48.3%	6.7%	42.9%	4.9%	44.7%
56	5.9%		4.3%		6.2%	
60	5.6%		4.5%		5.3%	
64	3.7%		3.8%		4.5%	
68	4.0%		4.5%		4.4%	
72	4.4%		4.3%		5.4%	
76	4.9%		3.2%		4.4%	
80	5.6%		4.7%		3.9%	
84	2.8%		2.4%		2.0%	
88	1.6%		2.0%		1.2%	
92	1.7%		0.6%		0.7%	
96	0.9%		0.8%		0.5%	
100	1.9%		1.2%		1.5%	

Appendix Table 24 Aggregated WHO-5 scores by students' average Virtual Learning Environment login events per module attempted between March and May

WHO-5 Score	0-49 logins N = 920		50-99 logins N = 1,403		More than 100 logins N = 1,163	
0	0.4%	18.2%	0.4%	16.2%	0.9%	14.3%
4	1.8%		0.7%		1.5%	
8	2.1%		2.8%		2.1%	
12	3.9%		2.5%		2.9%	
16	4.5%		4.2%		2.6%	
20	5.4%		5.6%		4.3%	
24	4.6%	14.2%	4.2%	15.6%	3.6%	15.1%
28	4.2%		5.6%		5.3%	
32	5.4%		5.8%		6.2%	
36	5.5%	21.6%	5.8%	24.9%	5.9%	24.9%
40	5.8%		7.3%		6.9%	
44	5.9%		5.5%		6.0%	
48	4.5%		6.3%		6.1%	
52	6.2%	46.0%	5.8%	43.3%	4.6%	45.7%
56	5.5%		5.2%		6.1%	
60	4.8%		5.6%		4.7%	
64	3.4%		4.1%		4.8%	
68	4.8%		4.4%		3.9%	
72	3.9%		4.6%		6.0%	
76	4.2%		3.8%		4.5%	
80	4.8%		4.8%		3.5%	
84	2.5%		1.5%		2.9%	
88	2.1%		1.1%		1.5%	
92	1.3%		0.6%		0.8%	
96	0.9%		0.6%		0.5%	
100	1.6%		1.1%		1.8%	

Appendix Table 25 Aggregated WHO-5 scores by the total hours spent on the Virtual Learning Environment per student between March and May

WHO-5 Score	0-99 hours N = 1,764		100-199 hours N = 971		More than 200 hours N = 751	
0	0.6%	17.0%	0.5%	16.5%	0.5%	13.4%
4	1.4%		1.4%		0.8%	
8	2.3%		2.6%		2.3%	
12	3.3%		2.3%		3.3%	
16	4.0%		4.3%		2.3%	
20	5.3%		5.4%		4.3%	
24	4.1%	14.0%	4.5%	17.0%	3.5%	15.2%
28	4.4%		6.0%		5.9%	
32	5.5%		6.5%		5.9%	
36	5.3%	22.2%	6.0%	25.6%	6.7%	26.4%
40	6.6%		7.5%		6.3%	
44	5.8%		5.6%		6.0%	
48	4.5%		6.6%		7.5%	
52	6.2%	46.9%	4.3%	40.9%	5.5%	45.0%
56	4.7%		6.5%		6.5%	
60	5.3%		5.6%		4.1%	
64	3.8%		4.0%		5.1%	
68	4.4%		4.3%		4.3%	
72	5.0%		4.1%		5.6%	
76	3.9%		3.6%		5.6%	
80	5.3%		3.2%		3.7%	
84	2.9%		1.6%		1.5%	
88	1.7%		1.3%		1.2%	
92	1.0%		0.7%		0.7%	
96	0.9%		0.1%		0.7%	
100	1.8%		1.4%		0.7%	

Appendix Table 26 Aggregated WHO-5 scores by the average amount of hours spent on the Virtual Learning Environment per student between March and May (per module attempted)

WHO-5 Score	0-49 hours N = 2,257		50-99 hours N = 852		More than 100 hours N = 377	
0	0.6%	16.9%	0.5%	14.6%	0.5%	14.3%
4	1.3%		1.1%		1.6%	
8	2.3%		2.3%		2.4%	
12	3.0%		2.9%		3.2%	
16	4.1%		3.5%		2.1%	
20	5.5%		4.2%		4.5%	
24	4.3%	14.3%	3.9%	18.2%	3.2%	13.0%
28	4.6%		6.8%		4.5%	
32	5.3%		7.5%		5.3%	
36	5.5%	22.9%	6.0%	24.9%	6.9%	28.9%
40	6.6%		7.5%		6.1%	
44	5.6%		5.5%		7.4%	
48	5.2%		5.9%		8.5%	
52	5.7%	45.9%	5.8%	42.4%	4.0%	43.8%
56	5.3%		6.2%		5.8%	
60	5.6%		4.3%		3.7%	
64	3.9%		3.5%		6.6%	
68	4.4%		4.6%		3.4%	
72	4.8%		4.2%		7.2%	
76	3.9%		4.2%		5.6%	
80	4.9%		3.4%		3.7%	
84	2.5%		2.1%		1.1%	
88	1.6%		1.4%		1.1%	
92	0.9%		1.1%		0.3%	
96	0.8%		0.4%		0.5%	
100	1.7%		1.2%		0.8%	

Appendix 3e: Results by engagement with support services via CRM

Appendix Table 27 Aggregated WHO-5 scores by the total support tickets raised by each student in CRM between September and March

<table>
<tr><th>WHO-5
Score</th><th colspan="2">No tickets
N = 3,202</th><th colspan="2">1 ticket
N = 466</th><th colspan="2">2 tickets
N = 65</th><th colspan="2">More than 3 tickets
N = 8</th></tr>
<tr><td>0</td><td>0.91%</td><td rowspan="6">18.9%</td><td>1.93%</td><td rowspan="6">26.2%</td><td>1.54%</td><td rowspan="6">29.2%</td><td>12.50%</td><td rowspan="6">25.0%</td></tr>
<tr><td>4</td><td>1.72%</td><td>2.36%</td><td>1.54%</td><td>0.00%</td></tr>
<tr><td>8</td><td>2.40%</td><td>3.65%</td><td>3.08%</td><td>0.00%</td></tr>
<tr><td>12</td><td>2.81%</td><td>4.51%</td><td>6.15%</td><td>0.00%</td></tr>
<tr><td>16</td><td>4.78%</td><td>7.30%</td><td>9.23%</td><td>0.00%</td></tr>
<tr><td>20</td><td>6.31%</td><td>6.44%</td><td>7.69%</td><td>12.50%</td></tr>
<tr><td>24</td><td>6.06%</td><td rowspan="3">19.5%</td><td>7.94%</td><td rowspan="3">23.0%</td><td>3.08%</td><td rowspan="3">10.8%</td><td>0.00%</td><td rowspan="3">0.0%</td></tr>
<tr><td>28</td><td>6.06%</td><td>5.58%</td><td>3.08%</td><td>0.00%</td></tr>
<tr><td>32</td><td>7.37%</td><td>9.44%</td><td>4.62%</td><td>0.00%</td></tr>
<tr><td>36</td><td>6.43%</td><td rowspan="4">25.8%</td><td>6.44%</td><td rowspan="4">24.2%</td><td>7.69%</td><td rowspan="4">23.1%</td><td>12.50%</td><td rowspan="4">50.0%</td></tr>
<tr><td>40</td><td>6.68%</td><td>6.65%</td><td>3.08%</td><td>12.50%</td></tr>
<tr><td>44</td><td>7.46%</td><td>5.15%</td><td>6.15%</td><td>25.00%</td></tr>
<tr><td>48</td><td>5.22%</td><td>6.01%</td><td>6.15%</td><td>0.00%</td></tr>
<tr><td>52</td><td>5.34%</td><td rowspan="13">35.8%</td><td>5.36%</td><td rowspan="13">26.6%</td><td>3.08%</td><td rowspan="13">36.9%</td><td>0.00%</td><td rowspan="13">25.0%</td></tr>
<tr><td>56</td><td>4.62%</td><td>3.65%</td><td>6.15%</td><td>0.00%</td></tr>
<tr><td>60</td><td>3.84%</td><td>2.79%</td><td>6.15%</td><td>12.50%</td></tr>
<tr><td>64</td><td>3.62%</td><td>2.58%</td><td>6.15%</td><td>0.00%</td></tr>
<tr><td>68</td><td>4.22%</td><td>2.58%</td><td>1.54%</td><td>0.00%</td></tr>
<tr><td>72</td><td>3.44%</td><td>2.79%</td><td>3.08%</td><td>0.00%</td></tr>
<tr><td>76</td><td>3.19%</td><td>1.50%</td><td>0.00%</td><td>0.00%</td></tr>
<tr><td>80</td><td>3.03%</td><td>1.72%</td><td>4.62%</td><td>0.00%</td></tr>
<tr><td>84</td><td>1.62%</td><td>1.07%</td><td>1.54%</td><td>0.00%</td></tr>
<tr><td>88</td><td>0.91%</td><td>0.86%</td><td>3.08%</td><td>12.50%</td></tr>
<tr><td>92</td><td>0.72%</td><td>0.43%</td><td>0.00%</td><td>0.00%</td></tr>
<tr><td>96</td><td>0.37%</td><td>0.43%</td><td>0.00%</td><td>0.00%</td></tr>
<tr><td>100</td><td>0.87%</td><td>0.86%</td><td>1.54%</td><td>0.00%</td></tr>
</table>

Appendix Table 28 Type of CRM support by WHO-5 Category Score in March

WHO-5 Score	*No Support (n = 3202)*	*Multiple Types (n = 54)*	*Mitigation (n = 60)*	*Welfare (n = 26)*	*Finance (n = 78)*	*Other (n = 89)*	*Change of Circumstances (n = 232)*
Major Depression (HAM-D Minor)(0 to 21)	18.9% (n = 606)	29.6% (n = 16)	26.7% (n = 16)	30.8% (n = 8)	14.1% (n = 11)	28.1% (n = 25)	28.9% (n = 67)
Minor Depression (HAM-D Minor)(22 to 33)	19.5% (n = 624)	11.1% (n = 6)	21.7% (n = 13)	30.8% (n = 8)	19.2% (n = 15)	19.1% (n = 17)	23.7% (n = 55)
Low Wellbeing (34 to 50)	25.8% (n = 826)	24.1% (n = 13)	30% (n = 18)	19.2% (n = 5)	24.4% (n = 19)	16.9% (n = 15)	26.7% (n = 62)
OK to Positive Wellbeing (Over 50)	35.8% (n = 1146)	35.2% (n = 19)	21.7% (n = 13)	19.2% (n = 5)	42.3% (n = 33)	36% (n = 32)	20.7% (n = 48)

Appendix Table 29 Aggregated WHO-5 scores by the total support tickets raised by each student in CRM between March and May

WHO-5 Score	No tickets N = 2,341		1 ticket N = 899		2 tickets N = 193		More than 3 tickets N = 53	
0	0.3%	11.7%	1.2%	23.5%	0.5%	29.5%	3.8%	32.1%
4	0.8%		2.2%		2.6%		1.9%	
8	1.5%		4.0%		4.7%		5.7%	
12	2.3%		4.3%		5.2%		5.7%	
16	2.8%		5.7%		5.2%		7.5%	
20	4.2%		6.0%		11.4%		7.5%	
24	3.5%	13.2%	5.0%	18.9%	7.3%	20.2%	3.8%	15.1%
28	4.6%		6.1%		6.7%		7.5%	
32	5.1%		7.8%		6.2%		3.8%	
36	5.1%	23.1%	7.0%	25.1%	8.3%	26.4%	5.7%	37.7%
40	6.2%		7.7%		7.3%		13.2%	
44	5.9%		5.1%		7.3%		5.7%	
48	5.9%		5.3%		3.6%		13.2%	
52	5.7%	51.9%	5.3%	32.5%	4.1%	23.8%	3.8%	15.1%
56	6.0%		5.0%		3.1%		5.7%	
60	5.9%		4.1%		2.1%		0.0%	
64	4.9%		2.8%		1.6%		1.9%	
68	5.2%		2.1%		4.7%		1.9%	
72	5.9%		3.1%		2.1%		0.0%	
76	5.0%		3.0%		0.5%		0.0%	
80	5.3%		2.8%		1.6%		0.0%	
84	2.6%		1.3%		2.1%		0.0%	
88	1.8%		1.0%		0.0%		0.0%	
92	0.9%		0.7%		0.5%		1.9%	
96	0.6%		0.7%		0.5%		0.0%	
100	1.9%		0.6%		1.0%		0.0%	

Appendix Table 30 Type of CRM support by WHO-5 Category Score in May

WHO-5 Score	*No Support (n = 2,341)*	*Multiple Types (n = 176)*	*Mitigation (n = 671)*	*Other (n = 167)*	*Change of Circumstances (n = 131)*
Major Depression (HAM-D Minor)(0 to 21)	11.7% (n = 275)	32.4% (n = 57)	27.6% (n = 185)	12.6% (n = 21)	16.8% (n = 22)
Minor Depression (HAM-D Minor)(22 to 33)	13.2% (n = 309)	19.3% (n = 34)	20.1% (n = 135)	10.8% (n = 18)	22.9% (n = 30)
Low Wellbeing (34 to 50)	23.1% (n = 541)	28.4% (n = 50)	26.2% (n = 176)	25.7% (n = 43)	21.4% (n = 28)
OK to Positive Wellbeing (Over 50)	51.9% (n = 1216)	19.9% (n = 35)	26.1% (n = 175)	50.9% (n = 85)	38.9% (n = 51)

Appendix 3f: Results by previous academic performance

September (continuing students only)

Appendix Table 31 WHO-5 labels by count of continuing students' grade category in September

WHO-5 Score	< 50 (Third) N = 2,936	50-60 (2:2) N = 2,056	60-70 (2:1) N = 2,308	70 + (First Class) N = 1,137
HAM-D/Major	5.8%	3.6%	3.2%	3.8%
HAM-D/Minor	7.1%	5.4%	5.2%	5.4%
Low Wellbeing	16.5%	15.0%	14.3%	13.0%
OK Wellbeing	70.7%	75.9%	77.3%	77.8%

Appendix Table 32 Aggregated WHO-5 scores by continuing students' count of failed modules in the previous academic year in September

WHO-5 Score	0 N = 7,692		1 N = 305		2 N = 114		3 or more N= 326	
0	0.2%	4.1%	0.3%	3.9%	1.8%	6.1%	0.6%	7.1%
4	0.2%		0.3%		1.8%		0.6%	
8	0.3%		0.3%		0.0%		0.3%	
12	0.8%		0.3%		1.8%		1.2%	
16	1.0%		0.3%		0.0%		2.8%	
20	1.7%		2.3%		0.9%		1.5%	
24	1.4%	5.8%	1.0%	3.6%	0.9%	3.5%	2.8%	11.7%
28	1.9%		1.3%		0.9%		4.3%	
32	2.5%		1.3%		1.8%		4.6%	
36	3.0%	15.1 %	2.0%	9.5%	1.8%	14.0%	2.8%	19.0%
40	4.0%		2.6%		7.9%		4.3%	
44	4.0%		2.0%		0.9%		6.1%	
48	4.1%		3.0%		3.5%		5.8%	
52	5.0%	74.9 %	3.3%	83.0 %	7.0%	76.3%	5.2%	62.3%
56	5.4%		3.9%		4.4%		5.5%	
60	6.9%		4.3%		3.5%		3.1%	
64	6.1%		7.2%		7.0%		6.4%	
68	7.1%		6.2%		9.6%		5.5%	
72	7.9%		7.9%		7.0%		6.4%	
76	7.7%		6.9%		6.1%		6.4%	
80	13.1 %		17.0 %		7.0%		5.2%	
84	4.5%		4.3%		6.1%		5.8%	
88	2.7%		4.9%		3.5%		3.1%	
92	1.9%		1.6%		4.4%		3.1%	
96	1.2%		2.6%		0.0%		1.5%	
100	5.3%		12.8 %		10.5 %		4.9%	

May

Appendix Table 33 WHO-5 labels by count of students' latest grade category in May

WHO-5 Score	0-10 N= 43	10-20 N= 12	20-30 N= 41	30-40 N= 78	40-50 N= 215	50-60 N= 608	60-70 N= 1023	70-80 N= 546	80-90 N= 138	90-100 N= 13	Data not available
HAM-D/Major	41.9%	58.3%	39.0%	26.9%	20.9%	19.7%	14.2%	15.0%	15.9%	23.1%	10.5%
HAM-D/Minor	20.9%	16.7%	22.0%	25.6%	15.3%	19.1%	14.5%	17.8%	15.2%	0.0%	9.2%
Low Wellbeing	20.9%	16.7%	19.5%	15.4%	29.3%	24.7%	27.1%	23.6%	23.9%	30.8%	19.6%
OK Wellbeing	16.3%	8.3%	19.5%	32.1%	34.4%	36.5%	44.3%	43.6%	44.9%	46.2%	60.6%

Appendix Table 34 Aggregated WHO-5 scores by students' count of failed modules in the previous Semester

WHO-5 Score	0 N = 3,384		1 N = 35		2 N = 40		3 or more N= 27		Data not available
0	0.5%	15.3%	2.9%	22.9%	5.0%	62.5%	3.7%	29.6%	
4	1.3%		2.9%		2.5%		0.0%		
8	2.2%		2.9%		12.5%		0.0%		
12	2.9%		8.6%		7.5%		3.7%		
16	3.6%		5.7%		7.5%		7.4%		
20	4.8%		0.0%		27.5%		14.8%		
24	4.0%	14.8%	11.4%	28.6%	0.0%	12.5%	18.5%	33.3%	
28	5.0%		11.4%		10.0%		7.4%		
32	5.9%		5.7%		2.5%		7.4%		
36	5.8%	24.2%	8.6%	22.9%	0.0%	7.5%	11.1%	25.9%	
40	6.9%		2.9%		2.5%		7.4%		
44	5.8%		5.7%		2.5%		3.7%		
48	5.8%		5.7%		2.5%		3.7%		
52	5.6%	45.6%	8.6%	25.7%	0.0%	17.5%	0.0%	11.1%	
56	5.6%		2.9%		5.0%		7.4%		
60	5.2%		0.0%		2.5%		3.7%		
64	4.2%		2.9%		0.0%		0.0%		
68	4.3%		2.9%		7.5%		0.0%		
72	5.1%		0.0%		0.0%		0.0%		
76	4.3%		2.9%		0.0%		0.0%		
80	4.5%		0.0%		2.5%		0.0%		
84	2.3%		0.0%		0.0%		0.0%		
88	1.5%		0.0%		0.0%		0.0%		
92	0.9%		0.0%		0.0%		0.0%		
96	0.7%		0.0%		0.0%		0.0%		
100	1.4%		5.7%		0.0%		0.0%		

Appendix 4: Clustering Analyses

Appendix 4a: Analysis of overlap ranges for hierarchical and K Means clustering

Appendix Table 35 Average score of question 1 "Over the last two weeks I have felt cheerful and in good spirits " within the overlap range for both clustering approaches

Aggregated WHO-5 Score	Hierarchical			K Means		
	Cluster 1	Cluster 2	Difference	Cluster 1	Cluster 2	Difference
32	2.4	1.9	0.5			
36	2.4	2.0	0.3			
40	2.3	2.1	0.1			
44	2.6	2.1	0.6			
52	3.1	2.6	0.5			
56	3.2	1.0	2.2	3.1	3.0	0.1
60	3.4	0.5	2.9	3.3	5.0	-1.7
64	3.6	1.0	2.6	3.5	2.0	1.5
68	3.7	2.0	1.7	3.7	5.0	-1.3

Appendix Table 36 Average score of question 2 "I have felt calm and relaxed" within the overlap range for both clustering approaches

Aggregated WHO-5 Score	Hierarchical			K Means		
	Cluster 1	Cluster 2	Difference	Cluster 1	Cluster 2	Difference
32	0.8	1.7	-0.9			
36	1.4	2.1	-0.7			
40	2.1	2.2	-0.2			
44	2.2	2.5	-0.3			
52	2.7	2.3	0.4			
56	2.8	2.8	0.0	2.8	2.6	0.1
60	3.0	3.5	-0.5	3.0	3.3	-0.4
64	3.1	3.5	-0.4	3.1	4.0	-0.9
68	3.4	3.0	0.4	3.4	5.0	-1.6

Appendix Table 37 Average score of question 3 "I have felt active and vigorous " within the overlap range for both clustering approaches

Aggregated WHO-5 Score	Hierarchical			K Means		
	Cluster 1	Cluster 2	Difference	Cluster 1	Cluster 2	Difference
32	1.6	1.4	0.2			
36	1.9	1.6	0.3			
40	1.9	1.8	0.1			
44	2.1	2.2	-0.2			
52	2.3	3.6	-1.2			
56	2.7	2.8	0.0	2.7	2.8	-0.1
60	2.9	3.0	-0.1	2.9	1.3	1.6
64	3.1	3.5	-0.4	3.1	5.0	-1.9
68	3.2	3.0	0.2	3.2	1.0	2.2

Appendix Table 38 Average score of question 4 "I woke up feeling fresh and rested " within the overlap range for both clustering approaches

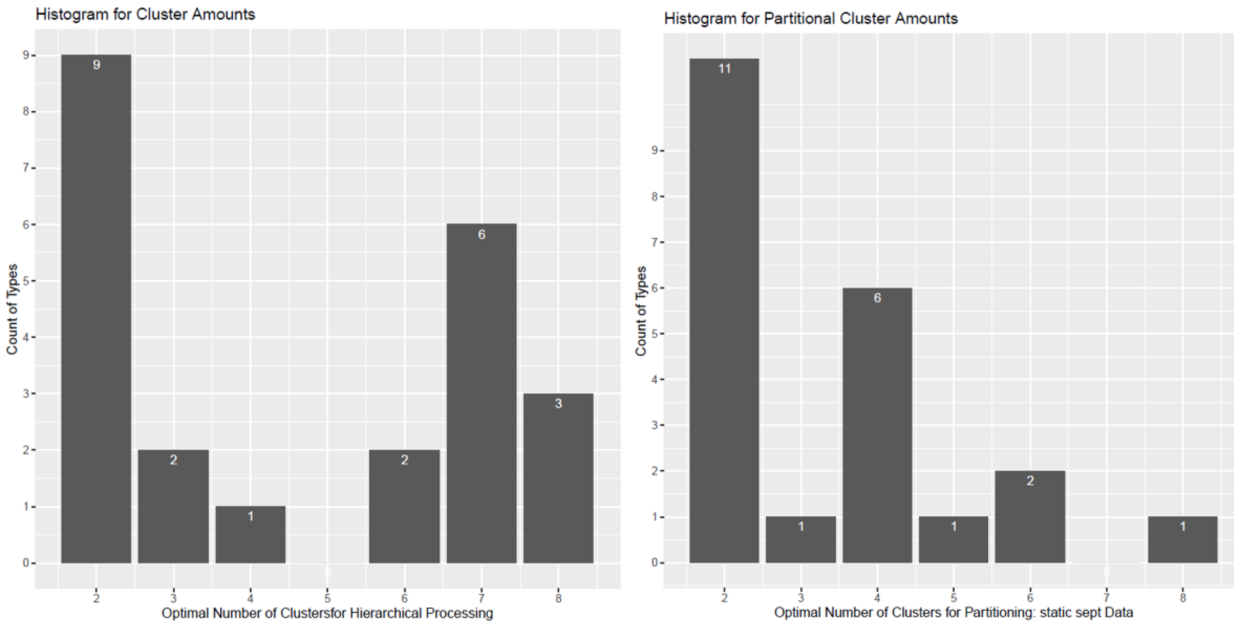
Aggregated WHO-5 Score	Hierarchical			K Means		
	Cluster 1	Cluster 2	Difference	Cluster 1	Cluster 2	Difference
32	1.4	1.3	0.1			

36	1.1	1.5	-0.4			
40	1.5	2.1	-0.7			
44	1.5	2.2	-0.8			
52	2.1	2.4	-0.4			
56	2.3	4.0	-1.7	2.4	1.6	0.8
60	2.7	3.5	-0.8	2.7	3.0	-0.3
64	2.9	3.5	-0.6	2.9	5.0	-2.1
68	3.2	4.0	-0.8	3.2	1.0	2.2

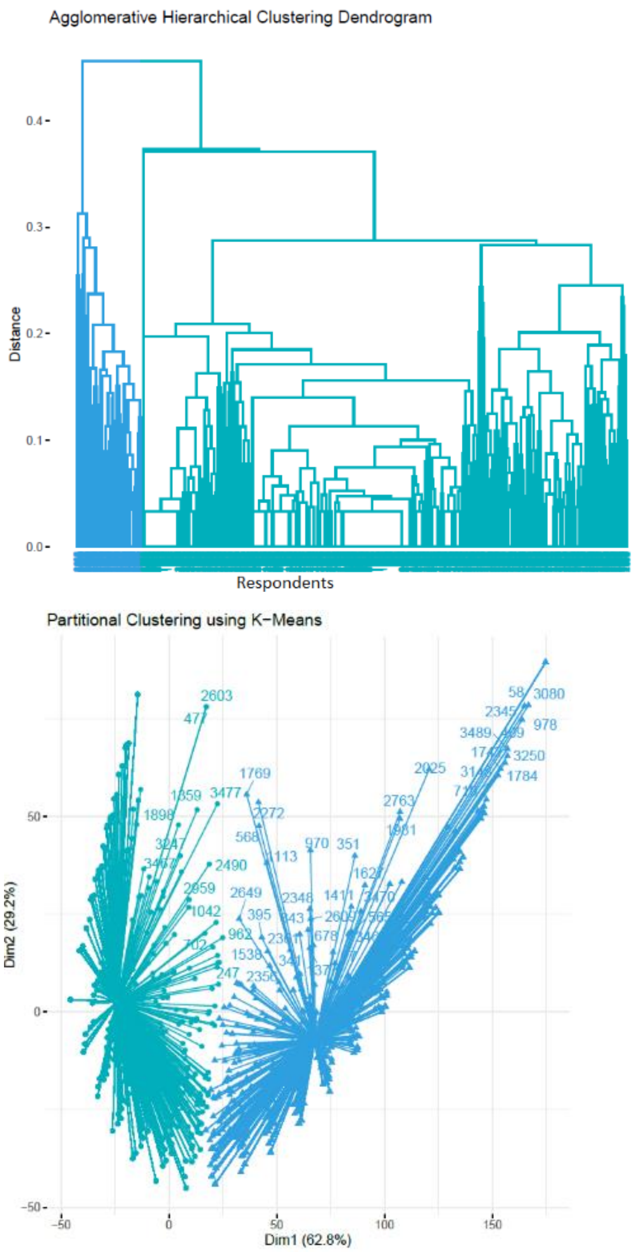
Appendix Table 39 Average score of question 5 "My daily life has been filled with things that interest me" within the overlap range for both clustering approaches

Aggregated WHO-5 Score	Hierarchical			K Means		
	Cluster 1	Cluster 2	Difference	Cluster 1	Cluster 2	Difference
32	1.8	1.6	0.2			
36	2.2	1.7	0.5			
40	2.2	1.7	0.5			
44	2.6	1.9	0.7			
52	2.9	2.1	0.7			
56	3.0	3.5	-0.5	3.0	3.9	-0.9
60	3.1	4.5	-1.4	3.1	2.3	0.8
64	3.4	4.5	-1.1	3.4	0.0	3.4
68	3.5	5.0	-1.5	3.5	5.0	-1.5

Appendix 4b: September clustering: WHO-5 Data only (also included in results)



Appendix Figure 3 Histograms showing optimal cluster amounts using NBClust for WHO-5 data only



Appendix Figure 4 Dendrogram and Partitional Cluster Diagram for September WHO-5 data

Appendix Table 40 September WHO-5 Sample Data Clusters

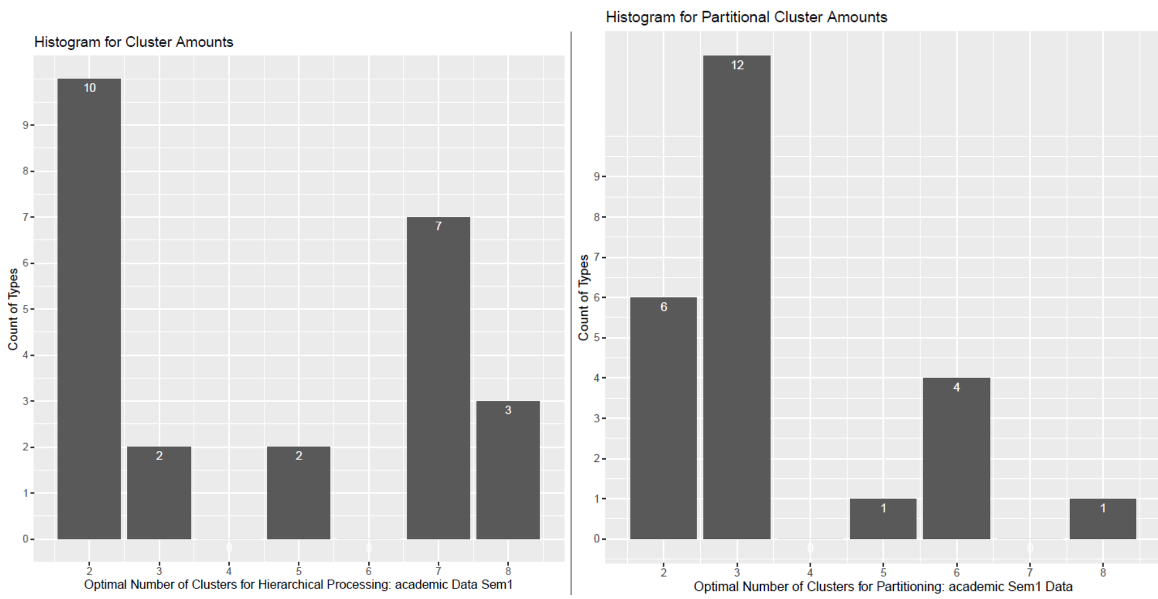
September Hierarchical WHO-5 Clusters

WHO-5	Hierarchical Cluster 1	Hierarchical Cluster 2
0		7
4		4
8		7
12		23
16		33
20		46
24		48
28		65
32	5	69
36	39	43
40	90	38
44	95	17
48	101	8
52	156	7
56	147	4
60	219	2
64	212	2
68	248	1
72	326	
76	309	
80	483	
84	194	
88	113	
92	72	
96	53	
100	214	
Total size of cluster	**3076**	**424**

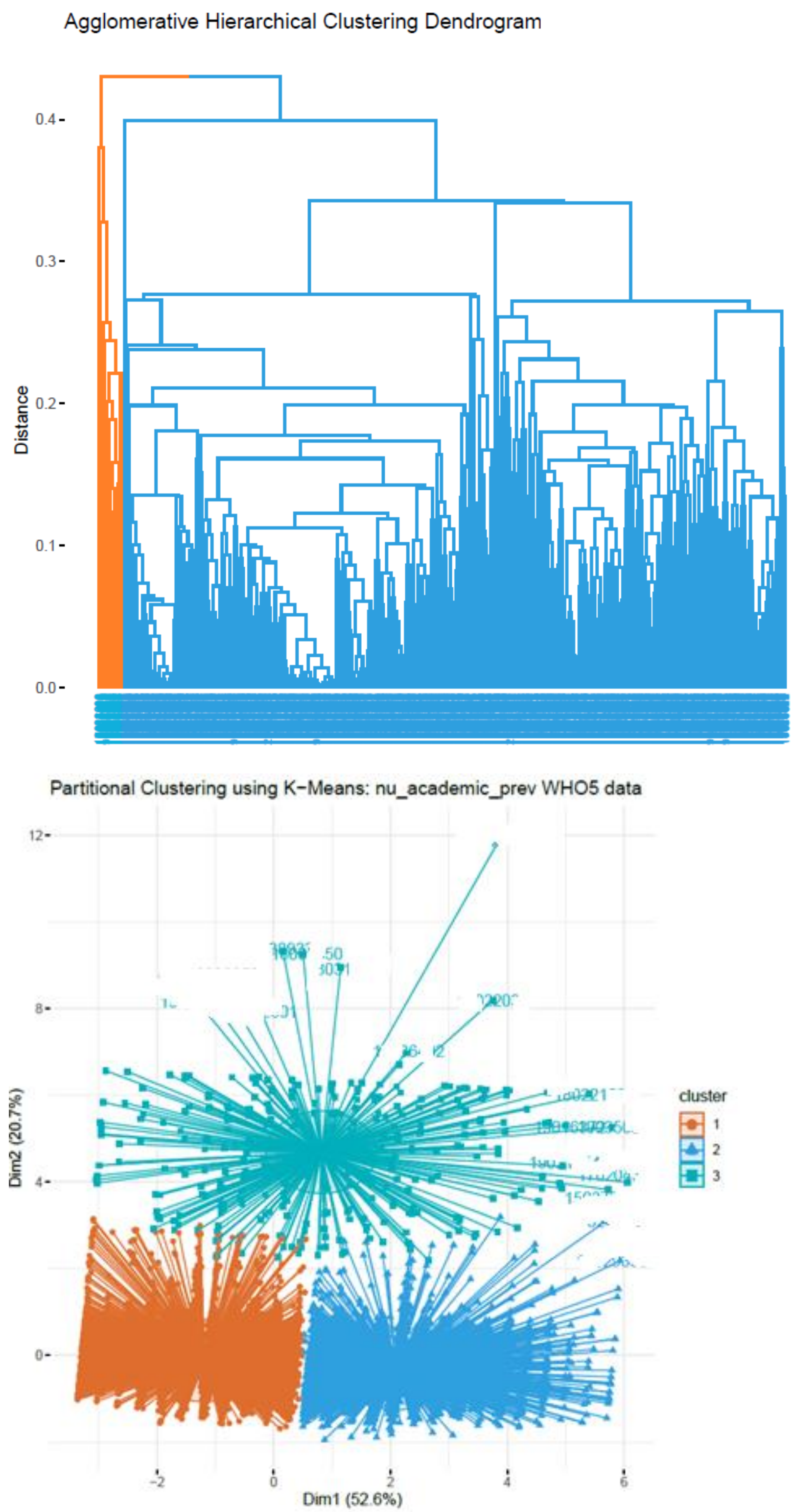
September Partitional WHO-5 Clusters

WHO-5	Partitional K Means 1	Partitional K Means 2
0		7
4		4
8		7
12		23
16		33
20		46
24		48
28		65
32		74
36		82
40		128
44		112
48		109
52		163
56	140	11
60	218	3
64	213	1
68	248	1
72	326	
76	309	
80	483	
84	194	
88	113	
92	72	
96	53	
100	214	
Total size of cluster	**2583**	**917**

Appendix 4c: September clustering: WHO-5 Data plus previous Academic performance



Appendix Figure 5 Histograms showing optimal cluster amounts using NBClust for WHO-5 data and previous academic data (all continuing students only)



Appendix Figure 6 Dendrogram and Partitional Cluster Diagram for September WHO-5 data plus previous academic data (all continuing students only)

Appendix Table 41 Clusters for September WHO-5 Clusters with previous academic data (all continuing students only)

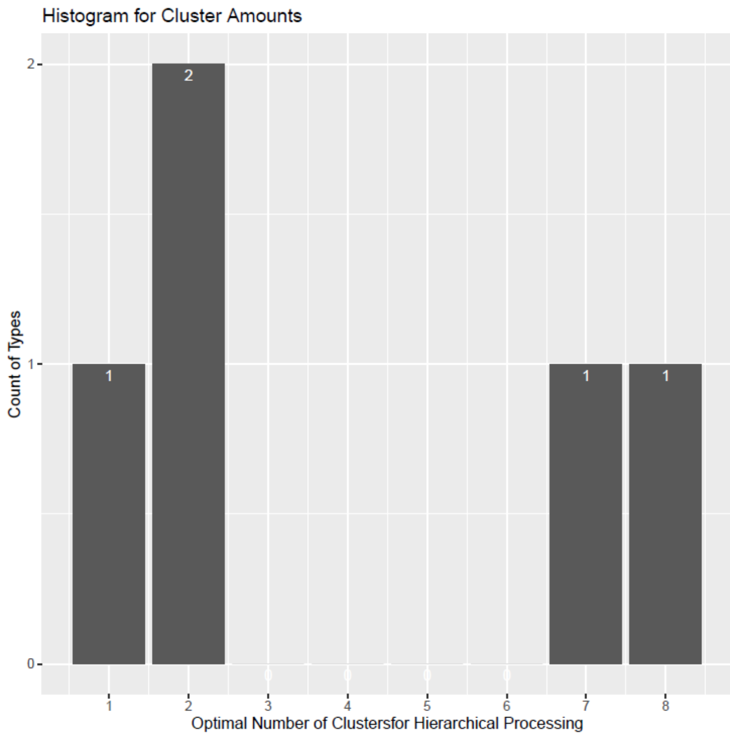
Hierarchical

WHO-5	Hierarchical Cluster 1	Hierarchical Cluster 2
0	17	4
4	14	4
8	24	1
12	65	6
16	75	9
20	136	6
24	109	10
28	151	15
32	199	17
36	237	11
40	319	22
44	311	21
48	327	24
52	399	23
56	436	14
60	554	2
64	520	1
68	595	
72	663	
76	642	
80	1088	
84	388	
88	237	
92	163	
96	107	
100	471	
Total size of cluster	**8247**	**190**

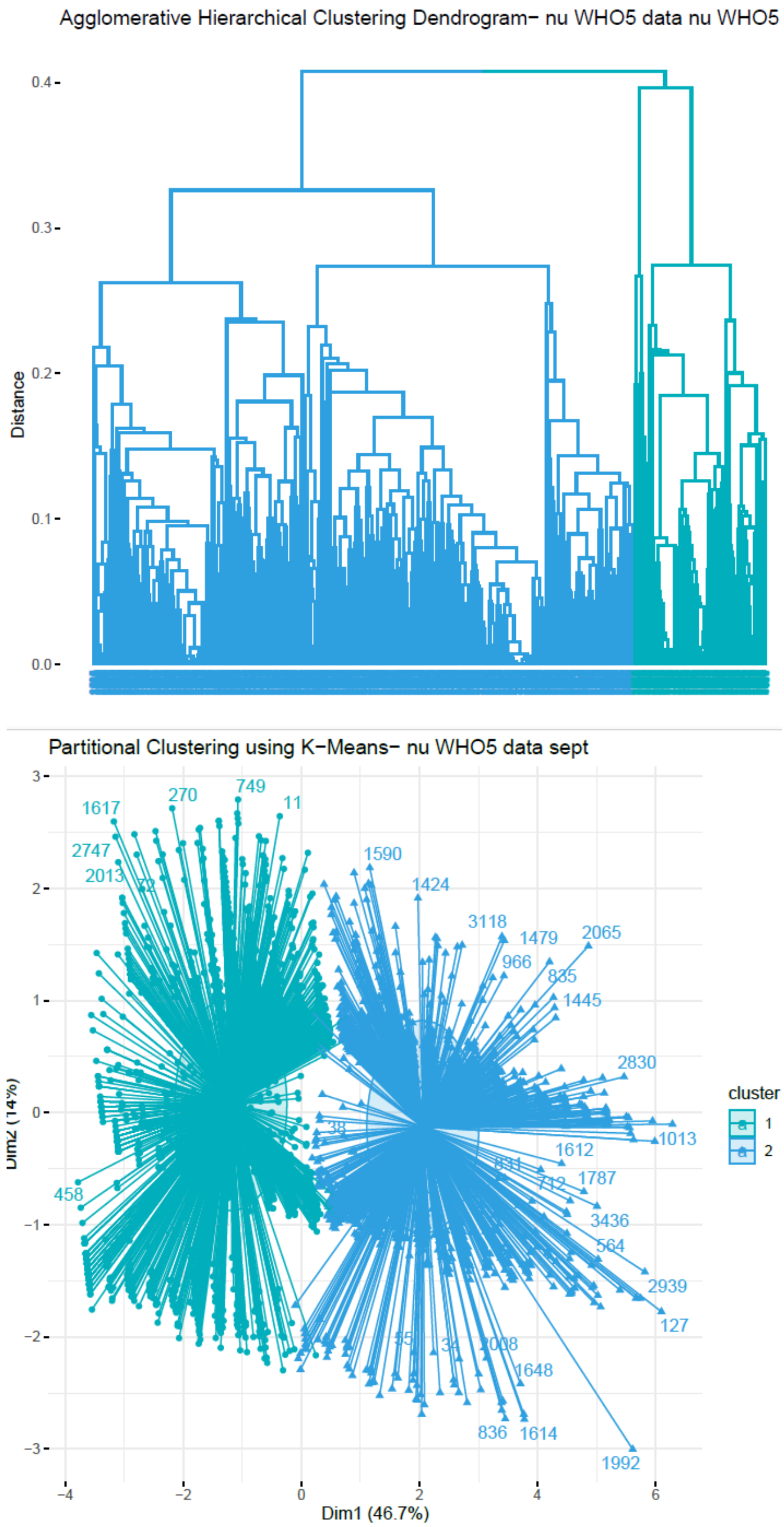
Partitional

WHO-5	Partitional K Means 1	Partitional K Means 2	Partitional K Means 3
0			21
4			18
8			25
12			71
16			84
20			142
24			119
28			166
32			216
36			248
40			341
44		21	311
48		181	170
52		391	31
56		449	1
60		556	
64		521	
68	11	584	
72	662	1	
76	642		
80	1088		
84	388		
88	237		
92	163		
96	107		
100	471		
Total size of cluster	3769	2704	1964

Appendix 4d: September clustering: WHO-5 Data plus Demographic data



Appendix Figure 7 Histograms showing optimal cluster amounts using NBClust for WHO-5 data and demographic data- Hierarchical only as partitional cannot be computed due to categorical variables (Gender and Fee Status)



Appendix Figure 8 Dendrogram and Cluster Diagram for September WHO-5 data plus demographic data

Appendix Table 42 Clusters for September WHO-5 data with demographic data

Hierarchical

WHO-5	Hierarchical Cluster 1	Hierarchical Cluster 2
0	2	2
4	5	
8	8	2
12	22	1
16	25	1
20	31	6
24	38	4
28	55	5
32	66	7
36	83	3
40	104	16
44	118	5
48	119	13
52	146	12
56	160	17
60	189	29
64	201	18
68	208	48
72	271	57
76	240	56
80	386	114
84	131	46
88	57	41
92	37	45
96	28	30
100	90	102
Total size of cluster	**2820**	**680**

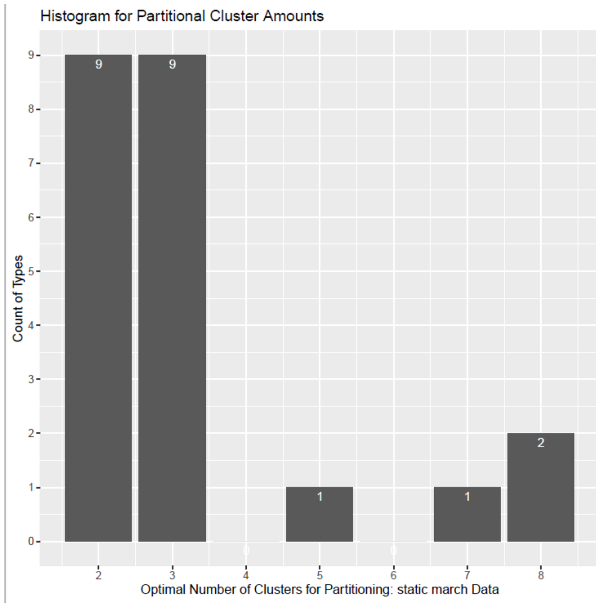
Partitional

WHO-5	Partitional K Means 1	Partitional K Means 2	Partitional K Means 3
0			4
4			5
8			10
12			23
16			26
20			37
24			42
28			60
32			73
36			86
40			120
44		2	121
48		11	121
52		98	60
56		160	17
60	2	214	2
64	16	203	
68	53	203	
72	183	145	
76	267	29	
80	498	2	
84	177		
88	98		
92	82		
96	58		
100	192		
Total size of cluster	1626	1067	807

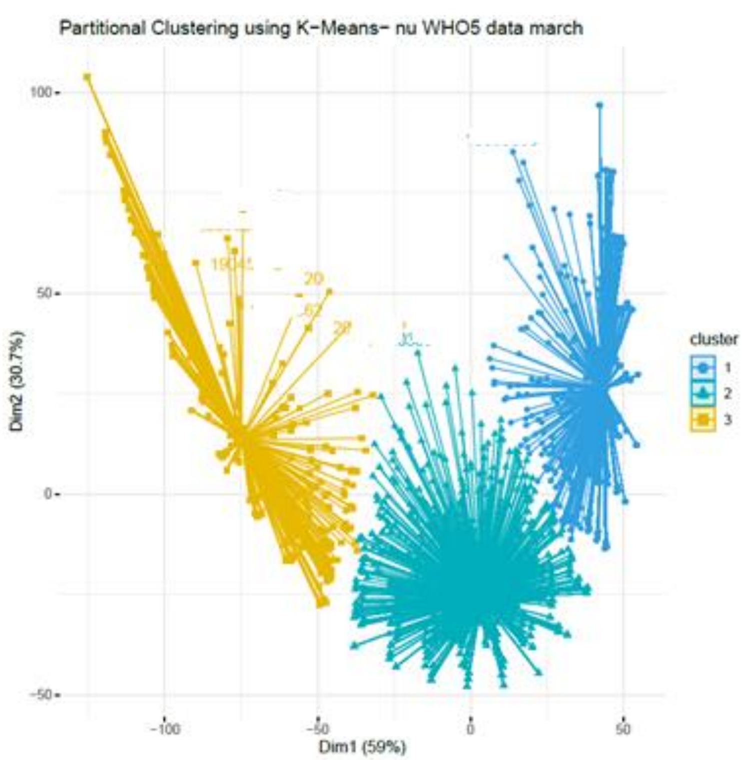
Appendix 4e: March clustering: WHO-5 Data Only

Appendix Table 43 Partitional clusters for March WHO-5 data only

WHO-5	Partitional Cluster 1	Partitional Cluster 2	Partitional Cluster 3
0	40		
4	67		
8	96		
12	115		
16	193		
20	238		
24	233		
28	222		
32	1	282	
36		242	
40		248	
44		269	
48		199	
52		198	
56		169	
60		67	74
64			132
68			148
72			125
76			109
80			108
84			58
88			36
92			25
96			14
100			33
Total size of cluster	1205	1674	862



Appendix Figure 9 Histograms showing optimal cluster amounts using NBClust for March WHO-5 data only

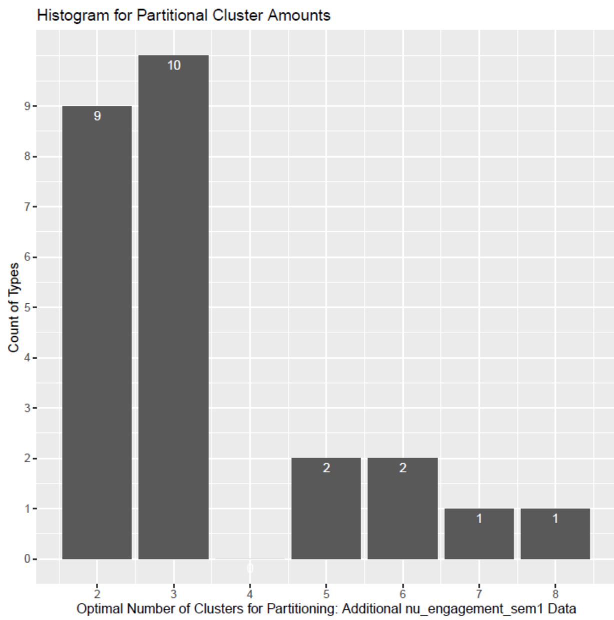


Appendix Figure 10 Partitional Cluster Diagram using K means for March WHO-5 data only

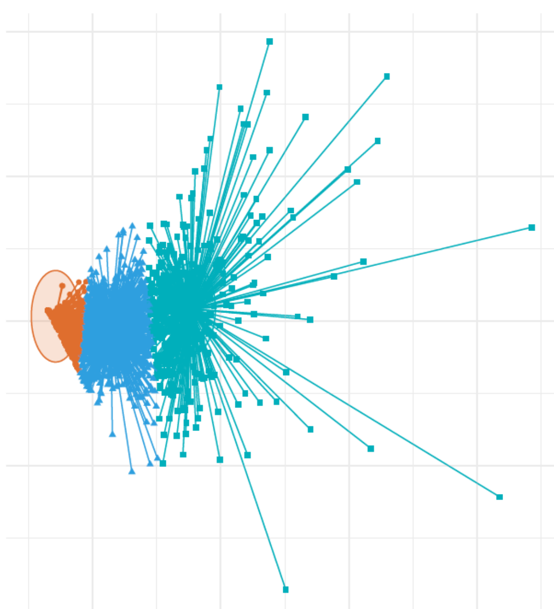
Appendix 4f: March clustering: WHO-5 Data plus VLE data

Appendix Table 44 Partitional clusters for March WHO-5 data with VLE Engagement data

WHO-5	Partitional Cluster 1	Partitional Cluster 2	Partitional Cluster 3
0		39	1
4		64	3
8		89	7
12		102	13
16		169	24
20		199	39
24		190	43
28		186	36
32		214	69
36		188	54
40		184	64
44		187	82
48	85	40	74
52	122		76
56	124		45
60	107		34
64	100		32
68	111		37
72	96		29
76	89		20
80	100		8
84	51		7
88	33		3
92	23		2
96	12		2
100	32		1
Total size of cluster	**1085**	**1851**	**805**



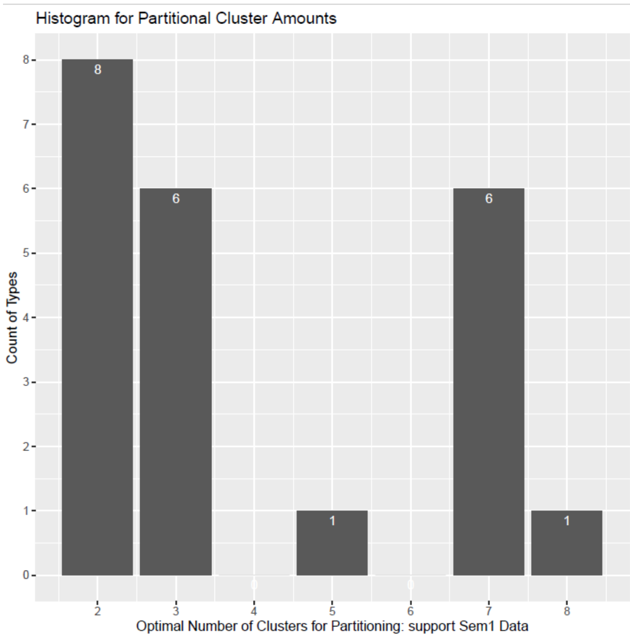
Appendix Figure 11 Histograms showing optimal cluster amounts using NBClust for



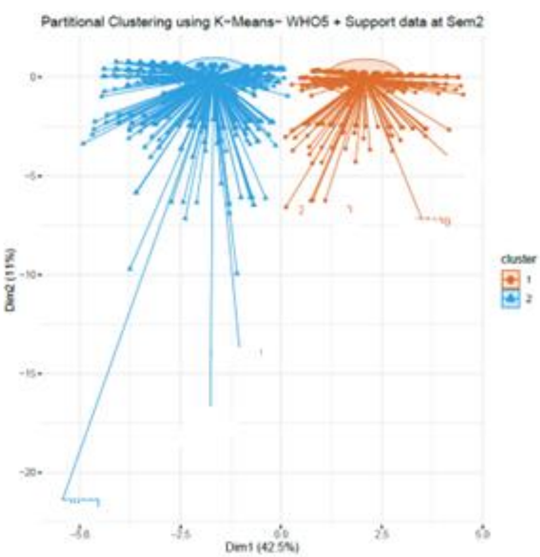
Appendix Figure 12 Cluster Diagram for March WHO-5 data plus VLE engagement data

Appendix 4g: March clustering: WHO-5 Data plus CRM data

Appendix Table 45 Partitional clusters for March WHO-5 data with CRM support data



Appendix Figure 13 Histograms showing optimal cluster amounts using NBClust



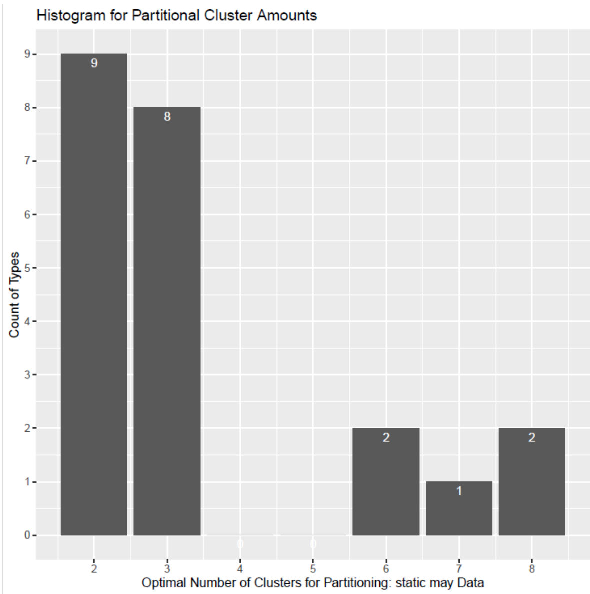
WHO-5	Hierarchical Cluster 1	Hierarchical Cluster 2
0	40	
4	67	
8	96	
12	115	
16	193	
20	238	
24	233	
28	222	
32	283	
36	242	
40	248	
44	269	
48	28	171
52	3	195
56		169
60		141
64		132
68		148
72		125
76		109
80		108
84		58
88		36
92		25
96		14
100		33
Total size of cluster	**2277**	**1464**

Appendix Figure 14 Partitional Cluster Diagram using K means for March WHO-5 data and CRM support Data

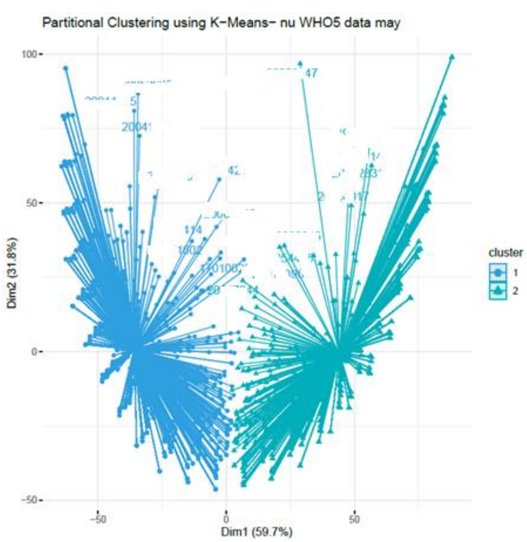
Appendix 4h: May clustering: WHO-5 Data

Appendix Table 46 Partitional clusters for May WHO-5 data only

WHO-5	Partitional Cluster 1	Partitional Cluster 2
0	20	
4	45	
8	82	
12	105	
16	130	
20	178	
24	143	
28	179	
32	204	
36	201	
40	236	
44	201	
48	196	4
52	3	189
56		195
60		178
64		144
68		151
72		171
76		145
80		153
84		78
88		52
92		30
96		22
100		51
Total size of cluster	1923	1563



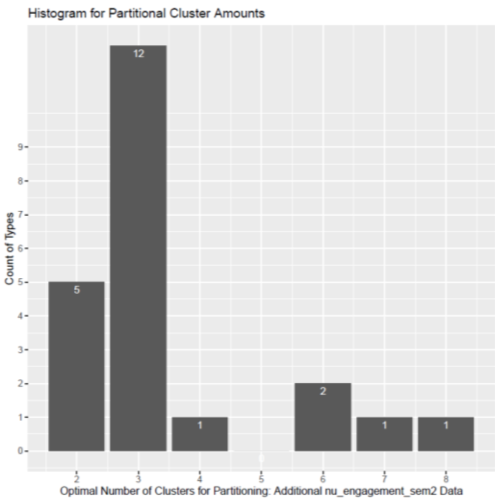
Appendix Figure 15 Histograms showing optimal cluster amounts using NBClust for May WHO-5 data only



Appendix Figure 16 Partitional Cluster Diagram using K means for May WHO-5 data only

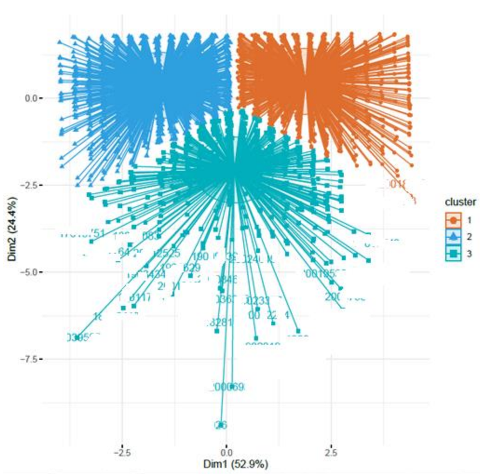
Appendix 4i: May clustering: WHO-5 Data plus VLE data

Appendix Table 47 Partitional clusters for May WHO-5 data with VLE Engagement data



Appendix Figure 17 Histograms showing optimal cluster amounts using NBClust for May WHO-5 data and VLE engagement data

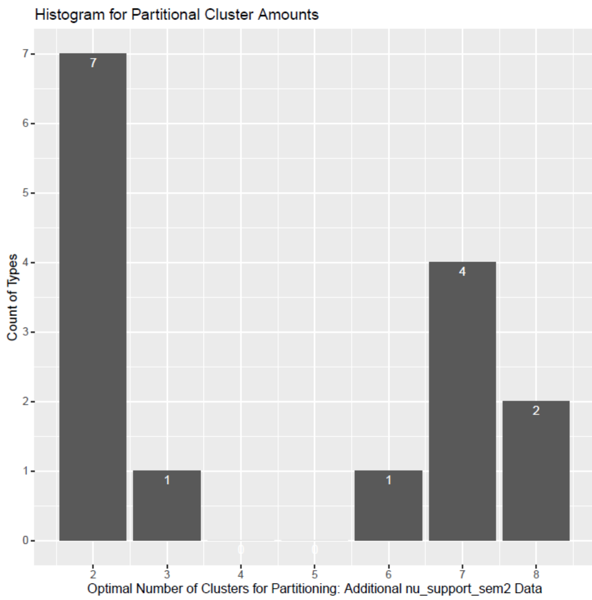
WHO-5	Partitional Cluster 1	Partitional Cluster 2	Partitional Cluster 3
0			20
4			45
8			82
12			105
16			130
20			178
24			143
28	11		168
32	53		151
36	138		63
40	214		22
44	199		2
48	200		
52	192		
56	195		
60	169	9	
64	58	86	
68	3	148	
72		171	
76		145	
80		153	
84		78	
88		52	
92		30	
96		22	
100		51	
Total size of cluster	**1432**	**945**	**1109**



Appendix Figure 18 Partitional Cluster Diagram using K means for May WHO-5 data plus VLE Engagement data

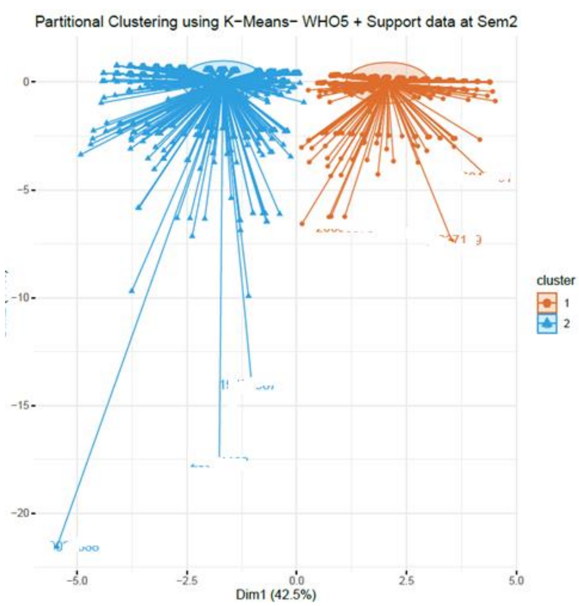
Appendix 4j: May clustering: WHO-5 Data plus CRM data

Appendix Table 48 Partitional clusters for May WHO-5 data with CRM Support data



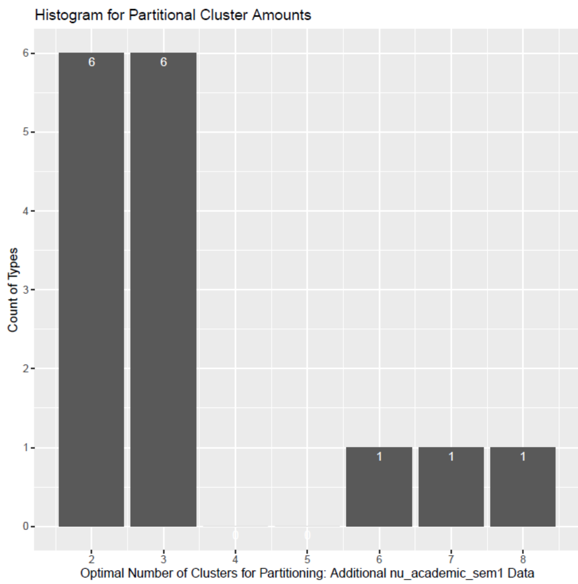
Appendix Figure 19 Histograms showing optimal cluster amounts using NBClust for May WHO-5 data and CRM Support data

WHO-5	Partitional Cluster 1	Partitional Cluster 2
0	20	
4	45	
8	82	
12	105	
16	130	
20	178	
24	143	
28	179	
32	204	
36	201	
40	236	
44	201	
48	61	139
52	7	185
56	2	193
60		178
64		144
68		151
72		171
76		145
80		153
84		78
88		52
92		30
96		22
100		51
Total size of cluster	**1794**	**1692**

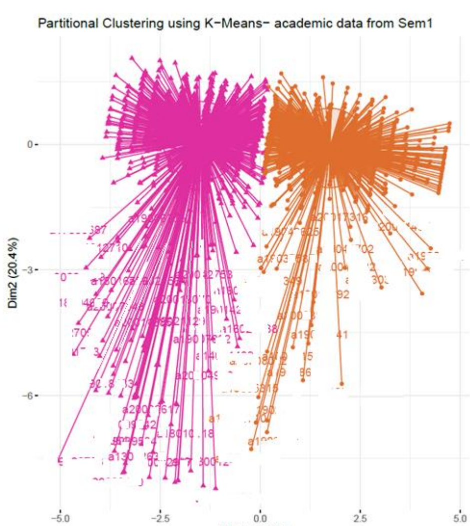


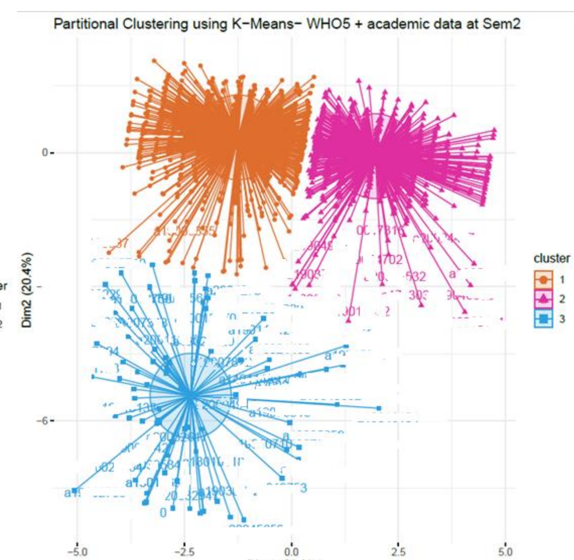
Appendix Figure 20 Cluster Diagram for May WHO-5 data plus CRM Support data

Appendix 4k: May clustering: WHO-5 Data plus previous academic performance



Appendix Figure 21 Histograms showing optimal cluster amounts using NBClust for May WHO-5 data and Semester 1 academic data





Appendix Figure 22 Cluster Diagrams for May WHO-5 data plus previous academic data from Semester 1 (2 and 3 cluster variants)

Appendix Table 49 Clusters for May WHO-5 data with academic data

K Means with 2 clusters

WHO-5	Partitional K Means 1	Partitional K Means 2
0		20
4		39
8		73
12		92
16		106
20		149
24		120
28		156
32		179
36		172
40		197
44	1	151
48	151	15
52	143	
56	141	
60	130	
64	102	
68	108	
72	125	
76	101	
80	94	
84	53	
88	34	
92	19	
96	10	
100	36	
Total size of cluster	**1248**	**1469**

K Means with 3 clusters

WHO-5	Partitional K Means 1	Partitional K Means 2	Partitional K Means 3
0	4	16	
4	2	37	
8	5	68	
12	7	85	
16	5	101	
20	15	134	
24	7	113	
28	9	147	
32	4	175	
36	3	169	
40	3	194	
44	3	149	
48	3	163	
52			143
56	4		137
60	2		128
64	1		101
68	3		105
72			125
76			101
80	1		93
84			53
88			34
92			19
96			10
100			36
Total size of cluster	**81**	**1551**	**1085**

References

Adams, W.C. (1994) Conducting Semi-Structured Interviews in *Handbook of Practical Programme Evaluation*, Eds. Wholey, J.S., Hatry, H.P. and Newcomer., K.E.

Ahern, S., J. (2018) The potential and pitfalls of learning analytics as a tool for supporting student wellbeing. *Journal of Learning and Teaching in Higher Education*, 1 (2)

Aldalaykeh, M., Al-Hammouri, M. M., and Rababah, J. (2019). Predictors of mental health services help-seeking behavior among university students. *Cogent Psychology*, 6(1), 1660520.

Aleven, V., and Koedinger, K. R. (2000). Limitations of student control: Do students know when they need help?. In *Intelligent Tutoring Systems: 5th International Conference, ITS 2000 Montréal, Canada, June 19–23, 2000 Proceedings 5* (292-303). Springer Berlin Heidelberg.

Anderson, J. M., Berc, L. M., Dean, J., Ghemawat, S., Henzinger, M. R., Leung, S. T. A., and Weihl, W. E. (1997). Continuous profiling: Where have all the cycles gone?. *ACM Transactions on Computer Systems* (TOCS), 15(4), 357-390.

Andrews, B., and Wilding, J. M. (2004). The relation of depression and anxiety to life-stress and achievement in students. Br*itish journal of psychology*, 95(4), 509–521. https://doi.org/10.1348/0007126042369802

Anshari, M., Almunawar, M. N., Lim, S. A., and Al-Mudimigh, A. (2019). Customer relationship management and big data enabled: Personalization and customization of services. *Applied Computing and Informatics*, 15(2), 94-101.

Arie, S. (2017). Simon Wessely: "Every time we have a mental health awareness week my spirits sink". BMJ, 358, j4305. https ://doi.org/10.1136/bmj.j4305 .

Arnold, K. E., and Sclater, N. (2017). Student perceptions of their privacy in leaning analytics applications. In *Proceedings of the seventh international learning analytics and knowledge conference* (66-69).

Ashton, J. (1998) The historical shift in public health in *Health promoting universities: concept, experience and framework for action*. Eds Tsouros, Dowding, Thompason and Dooris, Target 14 World Health Organization. Regional Office for Europe. https://apps.who.int/iris/handle/10665/108095, 5-10

Ayers, J. W., Althouse, B. M., Allem, J. P., Rosenquist, J. N., and Ford, D. E. (2013). Seasonality in seeking mental health information on Google. *American journal of preventive medicine,* 44(5), 520-525.

Baghramian, M. and Carter, J.A. (2021), Relativism, *The Stanford Encyclopaedia of Philosophy*, Edward N. Zalta (ed.)

Banks, B. (2018). University Mental Health Outreach Targeting Students of Color. *Journal Of College Student Psychotherapy*, 34(1), 78-86.

Barkham, M., Broglia, E., Dufour, G., Fudge, M., Knowles, L., and Percy, A. et al. (2019). Towards an evidence-base for student wellbeing and mental health: Definitions, developmental transitions and data sets. *Counselling And Psychotherapy Research*, 19(4), 351-357. https://doi.org/10.1002/capr.12227

Barthelmes, V. M., Li, R., Andersen, R. K., Bahnfleth, W., Corgnati, S. P., and Rode, C. (2018). Profiling occupant behaviour in Danish dwellings using time use survey data. *Energy and Buildings*, 177, 329-340.

Bartol, C. R., and Bartol, A. M. (2012). *Criminal and behavioral profiling*. Sage.

Batchelor, R., Pitman, E., Sharpington, A., Stock, M., and Cage, E. (2020). Student Perspectives on Mental Health Support and Services in the UK. Jou*rnal of Further and Higher Education*, 44(4), 483–497. https://doi.org/10.1080/0309877X.2019.1579896"

Beattie, A. (1998) Action learning for health on campus: muddling through with a model? in *Health promoting universities: concept, experience and framework for action*. Eds Tsouros, Dowding, Thompason and Dooris, Target 14 World Health Organization. Regional Office for Europe. https://apps.who.int/iris/handle/10665/108095, pp 45-56

Beer, D. G. (2017) The data analytics industry and the promises of real-time knowing: perpetuating and deploying a rationality of speed. *Journal of Cultural Economy*. 21-33. ISSN 1753-0369

Behboodi Moghadam, Z., Ordibeheshti Khiaban, M., Esmaeili, M., and Salsali, M. (2017). Motherhood challenges and well-being along with the studentship role among

Iranian women: A qualitative study. *International journal of qualitative studies on health and well-being*, 12(1), 1335168.

Ben-David, V. (2021). The Experience of Student-Mothers in an Israeli College: An Empirical Examination. *Journal of Student Affairs Research and Practice*, 58(5), 574-587.

Bewick, B., Gill, J., Mulhern, B., Barkham, M. and Hill, A. (2008) Using electronic surveying to assess psychological distress within the UK university student population: a multi-site pilot investigation, *E-Journal of Applied Psychology*: 4(2): 1-5

Bewick, B., Koutsopoulou, G., Miles, J., Slaa, E. and Barkham, M. (2010) Changes in undergraduate students' psychological well-being as they progress through university, *Studies in Higher Education*, 35:6, 633-645, DOI: 10.1080/03075070903216643

Bharti, N. (2022). Engaging Critically with Algorithms: Conceptual and Performative Interventions. *Science, Technology, and Human Values*, 47(4), 833–851. https://doi.org/10.1177/01622439211015296

Bilgrami, A. (2002). Realism and relativism. *Philosophical issues*, *12*, 1-25.

Blom, B. and Morén, S. (2011) Analysis of Generative Mechanisms, *Journal of Critical Realism*, 10:1, 60-79, DOI: 10.1558/jcr.v10i1.60

Blumenstein, M. (2020). Synergies of Learning Analytics and Learning Design: A Systematic Review of Student Outcomes. *Journal of Learning Analytics*, 7(3), 13-32.

Blumenstein, M., Liu, D. Y., Richards, D., Leichtweis, S., and Stephens, J. M. (2018). Data-informed nudges for student engagement and success. In *Learning Analytics in the Classroom* (185-207). Routledge.

Bond, R., Moorhead, A., Mulvenna, M., O'Neill, S., Potts, C. and Murphy, N. (2019) Exploring temporal behaviour of app users completing ecological momentary assessments using mental health scales and mood logs, *Behaviour and Information Technology*, 38:10, 016-1027, DOI: 10.1080/0144929X.2019.1648553

Bonynge, E. (1994) A Cluster Analysis Of Basic Personality Inventory (BPI) Adolescent Profiles, *Journal of Clinical Psychology*, 50:2

Boscaino, G., Sottile, G. and Adelfio, G. (2020) Migration and students' performance: detecting geographical differences following a curves clustering approach, *Journal of Applied Statistics*, DOI: 10.1080/02664763.2020.1845624

Boylan, M. (2011) Ethical Profiling, *Journal of Ethics*, (15),131–145, DOI 10.1007/s10892-010-9092-9

Bradbury, A., McGimpsey, I., and Santori, D. (2013). Revising rationality: the use of 'Nudge' approaches in neoliberal education policy. *Journal Of Education Policy*, 28(2), 247-267. https://doi.org/10.1080/02680939.2012.719638

Breet, E., Matooane, M., Tomlinson, M., and Bantjes, J. (2021). Systematic review and narrative synthesis of suicide prevention in high-schools and universities: a research agenda for evidence-based practice. *BMC public health*, 21(1), 1-21.

Briggs, A. R. J., Clark, J. and Hall, I. (2012). Building Bridges: Understanding Student Transition to University. *Quality in Higher Education* 18 (1): 3–21. doi:10.1080/13538322.2011.614468.

Broadbent, J. (2020). Am I just another number? Using online education innovations to personalise and improve the student experience in online learning. In Tertiary Online Teaching and Learning (13-24). Springer, Singapore.

Broglia, E., Ryan, G., Williams, C., Fudge, M., Knowles L., Turner, A., Dufour, G., Percy, A., Barkham, M. and on behalf of the SCORE Consortium (2021): Profiling student mental health and counselling effectiveness: lessons from four UK services using complete data and different outcome measures, *British Journal of Guidance and Counselling*, DOI: 10.1080/03069885.2020.1860191

Brown, A., Lawrence, J., Basson, M., Axelsen, M., Redmond, P., Turner, J., and Galligan, L. (2022). The creation of a nudging protocol to support online student engagement in higher education. *Active Learning in Higher Education*, 14697874211039077.

Brown, P. (2016) The Invisible Problem? Improving Students' Mental Health, *Higher Education Policy Institute Report*, September 2016, Brown J. S. L. (2018). Student mental health: some answers and more questions. *Journal of mental health (Abingdon, England)*, *27*(3), 193–196. https://doi.org/10.1080/09638237.2018.1470319

Bryman, A. (2016). *Social research methods* (Fifth ed.).

Bucher, T. (2012). Want to be on the top? Algorithmic power and the threat of invisibility on Facebook. *New Media and Society*, 14(7), 1164–1180. https://doi.org/10.1177/1461444812440159

Bucher, T. (2016). The algorithmic imaginary: exploring the ordinary affects of Facebook algorithms. *Information, Communication and Society*, 20(1), 30-44. doi: 10.1080/1369118x.2016.1154086

Bucher, T. (2018). *If... Then: Algorithmic Power and Politics*. Oxford: Oxford University Press.

Burt, K. B., Hay, D. F., Pawlby, S., Harold, G. and Sharp, D. (2004) The prediction of disruptive behaviour disorders in an urban community sample: the contribution of person-centred analyses., *Journal of Child Psychology and Psychiatry*, 45(6), 1159–1170

Byrom, N., Dinu, L., Kirkman, A., and Hughes, G. (2020). Predicting stress and mental wellbeing among doctoral researchers. *Journal Of Mental Health*, 1-9. doi: 10.1080/09638237.2020.1818196

Cage, E., Jones, E., Ryan, G., Hughes, G and Spanner, L (2021): Student mental health and transitions into, through and out of university: student and staff perspectives, *Journal of Further and Higher Education*, DOI: 10.1080/0309877X.2021.1875203

Canhoto, A. and Backhouse, J. (2008) General Description of the Process of Behavioural Profiling. in M. Hildebrandt and S. Gutwirth (Eds.), *Profiling the European Citizen: Cross-Disciplinary Perspectives* (1st. ed.). (47-64). Springer Publishing Company, Incorporated.

Cardwell, J., Lewis, E., Smith, K., Holt, E., Baillie, S., Allister, R., and Adams, V. (2013). A cross-sectional study of mental health in UK veterinary undergraduates. *Veterinary Record*, 173(11), 266-266. https://doi.org/10.1136/vr.101390

Carson, R. N., and Rowlands, S. (2001). A Critical Assessment of Dewey's Attack On Dualism. *The Journal of Educational Thought*, 35(1), 27–60. http://www.jstor.org/stable/23767387

Cawood, J., Dooris, M., and Powell, S. (2010). Healthy universities: Shaping the future. *Perspectives in Public Health*, 130(6), 259–260. https://doi.org/10.1177/1757913910384055

Chadha, D., Kogelbauer, A., Campbell, J., Hellgardt, K., Maraj, M., Shah, U., ... and Hale, C. (2021). Are the kids alright? Exploring students' experiences of support mechanisms to enhance wellbeing on an engineering programme in the UK. *European Journal of Engineering Educa*tion, 46(5), 662-677.

Charrad M., Ghazzali N., Boiteau V. and Niknafs, A. (2014). NbClust: An R Package for Determining the Relevant Number of Clusters in a Data Set., *Journal of Statistical Software*, 61(6), 1–36. https://www.jstatsoft.org/v61/i06/.

Chen, A.T., Wu, S.Y., Tomasino, K. N., Lattie, E. G. and Mohr, D. C. (2019) A multi-faceted approach to characterizing user behavior and experience in a digital mental health intervention, *Journal of Biomedical Informatics*, 94, 103187

Cheney-Lippold, J. (2017). *We Are Data: Algorithms and the Making of Our Digital Selves*., New York: New York University Press.

Chow, K. M., Tang, W. K. F., Chan, W. H. C., Sit, W. H. J., Choi, K. C., and Chan, S. (2018). Resilience and well-being of university nursing students in Hong Kong: a cross-sectional study. *BMC medical education*, 18(1), 1-8.

Clarke, R. (1994). The Digital Persona and its Application to Data Surveillance, *The Information Society*, Taylor and Francis Group, 10(2): 77-92.

Cleland, B. Wallace, J., Bond, R., Black, M., Mulvenna, M., Rankin, D. and Tanney, A. (2018) Insights into Antidepressant Prescribing Using Open Health Data, *Big Data Research*, 12, 41–48

Clow, D. (2013). An overview of learning analytics. *Teaching in Higher Education*, 18(6), 683-695.

Collis, J., and Hussey, R. (2003). Business research: *A practical guide for undergraduate and postgraduate students*.

Conley, C. S., Durlak, J. A., and Kirsch, A. C. (2015). A Meta-analysis of universal mental health prevention programs for higher education students. *Prevention science : the official journal of the Society for Prevention Research*, 16(4), 487–507. https://doi.org/10.1007/s11121-015-0543-1

Conley, C. S., J. B. Shapiro, B. M. Huguenel, and A. C. Kirsch. (2020) Navigating the College Years: Developmental Trajectories and Gender Differences in Psychological Functioning, Cognitive-Affective Strategies, and Social Well-Being, Eme*rging Adulthood*, 8 (2): 103–117. doi:10.1177/2167696818791603.

Connell, J., Barkham, M., and Mellor-Clark, J. (2008). The effectiveness of UK student counselling services: an analysis using the CORE System. *British Journal Of Guidance and Counselling*, 36(1), 1-18. doi: 10.1080/03069880701715655

Cooke, R., Barkham, M., Audin K., Bradley, M. and Davy, J. (2004) Student debt and its relation to student mental health, *Journal of Further and Higher Education*, 28:1, 53-66, DOI: 10.1080/0309877032000161814

Cormack, A. and Reeve, D. (2020) Code of practice for wellbeing and mental health analytics, *Jisc*, https://www.jisc.ac.uk/guides/code-of-practice-for-wellbeing-and-mental-health-analytics

Cormack, A. N., and Reeve, D. (2022). Developing a Code of Practice for Using Data in Wellbeing Support. Jou*rnal of Learning Analytics*, 1-12.

Cossy, L., S. (2014). Transition and Thriving in University: A Grounded Theory of the Transition Experiences and Conceptions of Thriving of a Selection of Undergraduate Students at Western University, *Electronic Thesis and Dissertation Repository*. 2531. https://ir.lib.uwo.ca/etd/2531

Coughlan, S. (2018). *Student suicide increase warning*. Retrieved from https://www.bbc.co.uk/news/education-43739863

Creed, P. A., French, J., and Hood, M. (2015). Working while studying at university: The relationship between work benefits and demands and engagement and well-being. *Journal of Vocational Behavior*, 86, 48-57.

Creswell, J. W., Plano Clark, V. L., Gutmann, M. L., & Hanson, W. E. (2003). Advanced mixed methods research designs. Handbook of mixed methods in social and behavioral research, 209(240), 209-240.

Creswell, J. W. (2009). Mapping the field of mixed methods research. *Journal of mixed methods research*, 3(2), 95-108.

Crick, T., Prickett, T., and Walters, J. (2021). A preliminary study exploring the impact of learner resilience under enforced online delivery during the COVID-19 pandemic. In *Proceedings of the 26th ACM Conference on Innovation and Technology in Computer Science Education* V. 2 (653-653).

Cruickshank, J. (2004). A tale of two ontologies: an immanent critique of critical realism. *The Sociological Review*, 52(4), 567-585.

Crook, C. and Garrett, D. (2004) The Positivist Paradigm in Contemporary Social Research in Research Methods, in *the Social Sciences* eds Somekh, B. ad Lewin, C. SAGE Publications (UK), 2004

Damgaard, M. T., and Nielsen, H. S. (2018). Nudging in education. *Economics of Education Review*, 64, 313-342.

Daniel, B. (2015). Big Data and analytics in higher education: Opportunities and challenges. *British journal of educational technology*, 46(5), 904-920.

Danowitz, A., and Beddoes, K. (2022). Mental Health in Engineering Education: Identifying Population and Intersectional Variation. *IEEE Transactions On Education*, 1-10. https://doi.org/10.1109/te.2022.3182626

Dart, S., and Spratt, B.(2021). Personalised emails in first-year mathematics: Exploring a scalable strategy for improving student experiences and outcomes, *Student Success*,12(1), 1-12, DOI: https://doi.org/10.5204/ssj.1543

De Vibe, M., Solhaug, I., Tyssen, R., Friborg, O., Rosenvinge, J. H., Sørlie, T., & Bjørndal, A. (2013). Mindfulness training for stress management: a randomised controlled study of medical and psychology students. *BMC medical education*, 13(1), 1-11.

de Wit, M., Pouwer, F., Gemke, R. J., Delemarre-van de Waal, H. A., and Snoek, F. J. (2007). Validation of the WHO-5 Well-Being Index in adolescents with type 1 diabetes. Diabetes Care: *The Journal of Clinical and Applied Research and Education*, 30(8), 2003-2006

Decuypere, M. and Landri, P. (2021) Governing by visual shapes: university rankings, digital education platforms and cosmologies of higher education, *Critical Studies in Education*, 62:1, 17-33, DOI: 10.1080/17508487.2020.1720760

Denzin, N. (2012) Triangulation 2.0, *Journal of Mixed Methods Research*, 6(2), 80–88

Dewey, J. (1929) *The Quest for Certainty: A Study of the Relation of Knowledge and Action,* Gifford Lectures, 1929 (at Edinburgh University).

Dewey, J. (1999) *The Essential Dewey*, eds. Hickman, L. and Alexander, T., Bloomington: Indiana University Press

Di Benedetto, M., Towt C.J. and Jackson, M.L (2020) A Cluster Analysis of Sleep Quality, Self-Care Behaviors, and Mental Health Risk in Australian University Students, *Behavioral Sleep Medicine*, 18:3, 309-320, DOI: 10.1080/15402002.2019.1580194

Dina, F. and Efklides, A. (2009) Student profiles of achievement goals, goal instructions and external feedback: Their effect on mathematical task performance and affect, *European Journal of Education and Psychology*, 2(3), 235-262

Doty, D. H., and Glick, W. H. (1994). Typologies as a Unique Form of Theory Building: Toward Improved Understanding and Modeling. *The Academy of Management Review*, 19(2), 230–251. https://doi.org/10.2307/258704

Dowding, G. and Thompson, T. (1998) Embracing organizational development for health promotion in higher education in *Health promoting universities: concept, experience and framework for action*. Eds Tsouros, Dowding, Thompason and Dooris, Target 14 World Health Organization. Regional Office for Europe. https://apps.who.int/iris/handle/10665/108095, 77-94

Downs, A., Boucher, L. A., Campbell, D. G., and Polyakov, A. (2017) Using the WHO-5 Well-Being Index to Identify College Students who are At-Risk for Mental Health Problems, *Psychological Sciences Faculty Publications and Presentations*. 9. https://pilotscholars.up.edu/psy_facpubs/9

Downs, A., Boucher, L. A., Campbell, D.G. and Dasse, M. (2013) Development and Initial Validation of the Symptoms and Assets Screening Scale, Jou*rnal of American College Health*, 61(3), 164-174, DOI: 10.1080/07448481.2013.773902

Drum, D. J., Brownson, C., Burton Denmark, A., and Smith, S. E. (2009). New data on the nature of suicidal crises in college students: Shifting the paradigm. *Professional Psychology: Research and Practice*, 40(3), 213–222. https://doi.org/10.1037/a0014465

Dummett, M. (1982). Realism. *Synthese*, 52(1), 55–112. http://www.jstor.org/stable/20115760

Durlak, J.A. (1997). Prevention of Behavioral and Social Problems. In: Successful Prevention Programs for Children and Adolescents. *Issues in Clinical Child Psychology*. Springer, Boston, MA. https://doi.org/10.1007/978-1-4899-0065-4_2

Durvasula, S., Lysonski, S., and Andrews, J. C. (1993). Cross-cultural generalizability of a scale for profiling consumers' decision-making styles. *Journal of Consumer Affairs*, 27(1), 55-65.

Earwaker, J. (1992) *Helping and Supporting Students*. Buckingham: Society for Research into Higher Education and Open University Press.

Edmonds, W., & Kennedy, T. (2017). *Exploratory-Sequential Approach*. SAGE Publications, Inc, https://doi.org/10.4135/9781071802779

Egger, S. A. (1999). Psychological profiling: Past, present, and future. *Journal of Contemporary Criminal Justice*, 15(3), 242-261.

Eisenberg, D., Downs, M. F., Golberstein, E., and Zivin, K. (2009). Stigma and help seeking for mental health among college students. *Medical Care Research and Review*, 66(5), 522-541.

Eisenberg, D., Golberstein, E., and Gollust, S. E. (2007). Help-Seeking and Access to Mental Health Care in a University Student Population. *Medical Care*, 45(7), 594–601. http://www.jstor.org/stable/40221479

Eisenberg, D., Gollust, S. E., Golberstein, E., and Hefner, J. L. (2007). Prevalence and correlates of depression, anxiety, and suicidality among university students. *The American journal of orthopsychiatry*, 77(4), 534–542. https://doi.org/10.1037/0002-9432.77.4.534

Eisenberg, D., Lipson, S.K. and Heinze, J. (2010) *The Healthy Minds Study*: Fall 2020 Data Report, available at https://healthymindsnetwork.org/wp-content/uploads/2021/02/HMS-Fall-2020-National-Data-Report.pdf, accessed on 14/07/2022

El Ansari, W., Stock, C., John, J., Deeny, P., Phillips, C., and Snelgrove, S. et al. (2011). Health Promoting Behaviours and Lifestyle Characteristics of Students at Seven

Universities in the UK. *Central European Journal Of Public Health*, 19(4), 197-204. doi: 10.21101/cejph.a3684

El-Den, S., Moles, R., Choong, H., and O'Reilly, C. (2020). Mental Health First Aid training and assessment among university students: A systematic review. *Journal Of The American Pharmacists Association*, 60(5), e81-e95. https://doi.org/10.1016/j.japh.2019.12.017

Esia-Donkoh, K. (2014). Child-rearing practices among student-mothers. *Society Biology and Human Affairs*, 78(1 and 2), 20–38. Retrieved from https://www.researchgate.net/publication/281117729_Child-rearing_practices_among_student-mothers_at_University_of_Cape_Coast_Ghana

Eskes, P., Spruit, M., Brinkkemper, S., Vorstman, J., and Kas, M. J. (2016). The sociability score: App-based social profiling from a healthcare perspective. *Computers in Human Behavior*, 59, 39-48.

Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. *American journal of theoretical and applied statistics*, *5*(1), 1-4.

European Quality of Life Survey. (2017). *Data visualisation* Retrieved 15 May 2022, from https://www.eurofound.europa.eu/data/european-quality-of-life-survey

Fergusson, D. M., Boden, J. M., & Horwood, L. J. (2007). Recurrence of major depression in adolescence and early adulthood, and later mental health, educational and economic outcomes. *The British Journal of Psychiatry*, *191*(4), 335-342.

Finlay, L. (2002). "Outing" the researcher: The provenance, process, and practice of reflexivity. *Qualitative health research*, 12(4), 531-545.

Foster, C. (2018). *A Realist Evaluation of a Learning Analytics Pilot Project*., Paper presented at the Advance HE Surveys Conference, Leeds, May 9. (16-28) available at https://s3.eu-west-2.amazonaws.com/assets.creode.advancehe-document-manager/documents/hea/private/hub/download/Advance%20HE%20Surveys%20Conference%202018%20-%20Learning%20analytics%20-%20Peter%20Francis%20and%20Carly%20Foster_1568037595.pdf

Foster, C. (2020). Students' Adoption of Learner Analytics., *Adoption of Data Analytics in Higher Education Learning and Teaching*, Springer, 10.1007/978-3-030-47392-1_8.

Foster, C., and Francis, P. (2019). A systematic review on the deployment and effectiveness of data analytics in higher education to improve student outcomes. *Assessment and Evaluation In Higher Education*, 45(6), 822-841. https://doi.org/10.1080/02602938.2019.1696945

Francis, P. and Foster, C. (2020) Thinking Critically and Realistically about the Platform University, Discover Society, available at https://postpandemicuniversity.net/2020/09/05/thinking-critically-and-realistically-about-the-platform-university/

Francis, P., Broughan, C., Foster, C. and Wilson, C. (2019) Thinking critically about learning analytics, student outcomes, and equity of attainment, Assessment and Evaluation in Higher Education, DOI: 10.1080/02602938.2019.1691975

Foucault, M. (1977) *Discipline and Punishment: the Birth of the Prison*. New York :Pantheon Books

Foucault, M. (1980) *Power/knowledge: Selected interviews and other writings*, 1972-1977. Vintage.

Freud, S. (1933). New Introductory Lectures on Psycho-Analysis. In J. Strachey et al. (Trans.), The Standard Edition of the Complete Psychological Works of Sigmund Freud, Volume XXII. London: Hogarth Press.

Fritsch, L. (2008) Profiling and Location-Based Services (LBS). in M. Hildebrandt and S. Gutwirth (Eds.), *Profiling the European Citizen: Cross-Disciplinary Perspectives* (1st. ed.). (147-168). Springer Publishing Company, Incorporated.

Fritz, J. (2017). Using analytics to nudge student responsibility for learning. *New Directions for Higher Education*, 2017(179), 65-75.

Gandomi, A., and Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. *International Journal Of Information Management*, 35(2), 137-144. https://doi.org/10.1016/j.ijinfomgt.2014.10.007

Gandrud, C. (2020) Repro*ducible Research with R and Rstudio*, 3rd Edition, Chapman and Hall

Givens, J. L., and Tjia, J. (2002). Depressed medical students' use of mental health services and barriers to use. *Academic medicine*, 77(9), 918-921.

Godwin, M. (2002) Reliability, Validity, and Utility of Criminal Profiling Typologies, *Journal of Police and Criminal Psychology*, 17(1)

Gogo, S., & Musonda, I. (2022). The Use of the Exploratory Sequential Approach in Mixed-Method Research: A Case of Contextual Top Leadership Interventions in Construction H&S. *International Journal of Environmental Research and Public Health*, *19*(12), 7276. MDPI AG. Retrieved from http://dx.doi.org/10.3390/ijerph19127276

Grant, A. (2006). Personal Tutoring: A System in Crisis? In: L. Thomas and P. Hixenbaugh (eds.) *Personal Tutoring in Higher Education*. Stoke on Trent: Trentham Books, 11-20.

Grineski, S., Morales, D., Collins, T., Nadybal, S. and Trego, S., 2021. Anxiety and depression among US college students engaging in undergraduate research during the COVID-19 pandemic. *Journal of American College Health*, 1-11.

Grossman, R. and Scala, K. (1993) Health Promotion and Organisational Development: Developing Settings for Health, *European Health Promotion Series* No. 2. WHO Europe/IFF Vienna.

Grover, V., Chiang, R. H.L., Liang, T. and Zhang, D. (2018) Creating Strategic Business Value from Big Data Analytics: A Research Framework, *Journal of Management Information Systems*, 35:2, 388-423, DOI: 10.1080/07421222.2018.1451951

Hamim, T., Benabbou, F., and Sael, N. (2019). Student profile modeling: an overview model. In *Proceedings of the 4th International Conference on Smart City Applications* (1-9).

Hardy, S. A., Francis, S. W., Zamboanga, B. L., Kim, S. Y., Anderson, S. G., and Forthun, L. F. (2013). The roles of identity formation and moral identity in college student mental health, health-risk behaviors, and psychological well-being. *Journal of clinical psychology*, 69(4), 364–382. https://doi.org/10.1002/jclp.21913

Harrer, M., Adam, S. H., Baumeister, H., Cuijpers, P., Karyotaki, E., Auerbach, R. P., Kessler, R. C., Bruffaerts, R., Berking, M., and Ebert, D. D. (2019). Internet interventions for mental health in university students: A systematic review and meta-analysis. *International journal of methods in psychiatric research*, 28(2), e1759. https://doi.org/10.1002/mpr.1759

Hathcoat, J. D., & Meixner, C. (2017). Pragmatism, factor analysis, and the conditional incompatibility thesis in mixed methods research. *Journal of Mixed Methods Research*, *11*(4), 433-449.

Hawkins, R., Kreuter, M., Resnicow, K., Fishbein, M., and Dijkstra, A. (2008). Understanding tailoring in communicating about health. *Health Education Research*, 23(3), 454-466. https://doi.org/10.1093/her/cyn004

Hazell, W. (2020) *Universities to get funding for student mental health 'innovations'*, The Independent: UK Edition, https://inews.co.uk/news/universities-funding-student-mental-health-minister-disclosing-mental-illness-parents-404883

Heiden - Rootes, K., Salas, J., Moore, R., Hasan, S., and Wilson, L. (2020). Peer victimization and mental health outcomes for lesbian, gay, bisexual, and heterosexual youth: A latent class analysis. *Journal of school health*, 90(10), 771-778.

Henman, Paul (2004) Targeted! Population Segmentation, Electronic Surveillance and Governing the Unemployed in Australia, *International Sociology* 19(2): 173-91.

Hildebrandt, M. (2008) Defining Profiling: A New Type of Knowledge?. in M. Hildebrandt and S. Gutwirth (Eds.), *Profiling the European Citizen: Cross-Disciplinary Perspectives* (1st. ed.). (17-46). Springer Publishing Company, Incorporated.

Hildebrandt, M. and Gutwirth, S. (2008) P*rofiling the European Citizen: Cross-Disciplinary Perspectives* (1st. ed.). Springer Publishing Company, Incorporated.

Hope, A., Dring, C., and Dring, J. (2005). *The health of Irish students: College Lifestyle and Attitudinal National (CLAN) Survey*. Dublin: Department of Health and Children

Hopkins, B. (1954). A new method for determining the type of distribution of plant individuals, *Annals of Botany*, 18(2), 213–227

https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/499475/Annex_B4_Mental_health_clustering_booklet.pdf

Huberty C.J., Jordan E.M. and Brandt W.C. (2005) Cluster Analysis in Higher Education Research. In: Smart J.C. (eds) *Higher Education: Handbook of Theory and Research. Higher Education: Handbook of Theory and Research*, vol 20. Springer, Dordrecht. https://doi.org/10.1007/1-4020-3279-X_8

Hughes, G., and Spanner, L. (2019). *The university mental health charter*. Leeds: Student Minds.

Hysenbegasi, A., Hass, S. L., and Rowland, C. R. (2005). The impact of depression on the academic productivity of university students. *The journal of mental health policy and economics*, 8(3), 145–151.

Ifenthaler, D., and Schumacher, C. (2016). Student perceptions of privacy principles for learning analytics. *Educational Technology Research and Development*, 64(5), 923–938. https://doi.org/10.1007/s11423-016-9477-y

Ivankova, N. V., Creswell, J. W., & Stick, S. L. (2006). Using mixed-methods sequential explanatory design: From theory to practice. *Field methods*, 18(1), 3-20.

Jacobsen, B. and Nørup, I. (2020) Young people's mental health: Exploring the gap between expectation and experience, *Educational Research*, 62(3), 249-265, doi: 10.1080/00131881.2020.1796516

Jain, A. K. , Duin, R. P. W. and Mao, J. (2000) Statistical pattern recognition: a review in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 22(1), doi: 10.1109/34.824819.

Jain, A. K. and Dubes, R. C (1988) *Algorithms for Clustering Data*, Prentice Hall., Englewood Cliffs, New Jersey

Johnson, R. B., and Onwuegbuzie, A. J. (2004). Mixed methods research: A research paradigm whose time has come. *Educational Researcher*, 33(7), 14-26.

Julal, F. (2013). Use of student support services among university students: associations with problem-focused coping, experience of personal difficulty and psychological distress. British *Journal Of Guidance and Counselling*, 41(4), 414-425. https://doi.org/10.1080/03069885.2012.741680

Julal, F. (2015). Predictors of undergraduate students' university support service use during the first year of university. *British Journal Of Guidance and*

Counselling, 44(4), 371-381. https://doi.org/10.1080/03069885.2015.1119232

Kassambara, A. (2017) *Practical Guide to Cluster Analysis in R: Unsupervised Machine Learning (Multivariate Analysis)* (Volume 1) 1st Edition, CreateSpace Independent Publishing Platform

Kim, E. H., Coumar, A., Lober, W. B., and Kim, Y. (2011). Addressing mental health epidemic among university students via web-based, self-screening, and referral system: A preliminary study. *IEEE Transactions on Information Technology in Biomedicine : A Publication of the IEEE Engineering in Medicine and Biology Society*, 15(2), 301-307.

King, N. (2004). Using templates in the thematic analysis of text. In C. Cassell and G. Symon (Eds.), *Essential guide to qualitative methods in organizational research,* 257–270. London, UK: Sage.

Kittel, B. (2006) A Crazy Methodology? On the Limits of Macro-Quantitative Social Science Research, *International Sociology*, 21(5), 647–677

Kleinberg, J., Ludwig, J., Mullainathan, S., and Sunstein, C. R. (2018). Discrimination in the Age of Algorithms. *Journal of Legal Analysis*, 10, 113-174.

Kreuter, M., Lukwago, S., Bucholtz, D., Clark, E., and Sanders-Thompson, V. (2003). Achieving Cultural Appropriateness in Health Promotion Programs: Targeted and Tailored Approaches. *Health Education and; Behavior*, 30(2), 133-146. https://doi.org/10.1177/1090198102251021

Krieger, T., Zimmermann, J., Huffziger, S., Ubl, B., Diener, C., Kuehner, C., & Holtforth, M. G. (2014). Measuring depression with a well-being index: further evidence for the validity of the WHO Well-Being Index (WHO-5) as a measure of the severity of depression. *Journal of affective disorders, 156*, 240-244.

Kristensen, D. B., and Ruckenstein, M. (2018). Co-evolving with self-tracking technologies. *New Media Society*, 20(10), 3624–3640. doi: https://doi.org/10.1177/1461444818755650

Kyndt , E., Dochy, F., Struyven, K. and Cascallar, E. (2012) Looking at learning approaches from the angle of student profiles, *Educational Psychology*, 32:4, 493-513, DOI: 10.1080/01443410.2012.667770

LaFrance. A. (2015) *Not Even the People Who Write Algorithms Really Know How They Work*, The Atlantic, published online 18th September 2015, available at https://www.theatlantic.com/technology/archive/2015/09/not-even-the-people-who-write-algorithms-really-know-how-they-work/406099/

Lal, R., Reaume, G., El Morr, C., and Khanlou, N. (2021). Mental health seeking behaviour of women university students: An intersectional analysis. *International Health Trends and Perspectives*, 1(2), 288-307.

Langford, R., Bonell, C., Jones, H., Pouliou, T., Murphy, S., Waters, E., Komro, K., Gibbs, L., Magnus, D., and Campbell, R. (2015). The World Health Organization's Health Promoting Schools framework: a Cochrane systematic review and meta-analysis. *BMC public health*, 15, 130. https://doi.org/10.1186/s12889-015-1360-y

Larcombe, W., Baik, C., and Finch, S. (2021). Exploring course experiences that predict psychological distress and mental wellbeing in Australian undergraduate and graduate coursework students. Hig*her Education Research and Development*, 1-16. https://doi.org/10.1080/07294360.2020.1865284

Lattie, E. G., Adkins, E. C., Winquist, N., Stiles-Shields, C., Wafford, Q. E., and Graham, A. K. (2019). Digital mental health interventions for depression, anxiety, and enhancement of psychological well-being among college students: systematic review. *Journal of medical Internet research*, 21(7), e12869.

Lawrence, J., Brown, A., Redmond, P., and Basson, M. (2019). Engaging the disengaged: Exploring the use of course-specific learning analytics and nudging to enhance online student engagement. *Student Success*, 10(2), 47-59.

Lewinsohn, P. M., Rohde, P., Seeley, J. R., & Fischer, S. A. (1993). Age-cohort changes in the lifetime occurrence of depression and other mental disorders. *Journal of Abnormal Psychology, 102*(1), 110–120. https://doi.org/10.1037/0021-843X.102.1.110

Li, W., Dorstyn, D., and Denson, L. (2014). Psychosocial correlates of college students' help-seeking intention: A meta-analysis. *Professional Psychology: Research And Practice*, 45(3), 163-170. https://doi.org/10.1037/a0037118

Li, Z., and de Rijke, M. (2017, August). The impact of linkage methods in hierarchical clustering for active learning to rank. In *Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval*, 941-944

Lin, Y. K., Chen, H., Brown, R. A., Li, S. H., and Yang, H. J. (2017). Healthcare predictive analytics for risk profiling in chronic care: A Bayesian multitask learning approach. *Mis Quarterly*, 41(2).

Lipton, P. (1991) *Inference to the Best Explanation*, Routledge, London

Lyon, D. (2002) Everyday Surveillance: Personal data and social classifications. *Information, Communication and Society*, 5:2, 242-257, DOI: 10.1080/13691180210130806

Macaskill, A. (2013) The mental health of university students in the United Kingdom. British *Journal of Guidance and Counselling*, (41)4, 426-441, http://dx.doi.org/10.1080/03069885.2012.743110

Malthus, T. (1798) *An Essay on the Principle of Popula*tion, Electronic Scholarly Publishing Project 1998

Manze, M., Watnick, D. and Freudenberg, N. (2021) How do childcare and pregnancy affect the academic success of college students?, *Journal of American College Health*, DOI: 10.1080/07448481.2021.1895174

Martin, J.M. (2010) Stigma and student mental health in higher education, *Higher Education Research and Development*, 29(3), 259–274

Martínez, I. M., Youssef-Morgan, C.M., Chambel, M.J. and Marques-Pinto, A. (2019) Antecedents of academic performance of university students: academic engagement and psychological capital resources, *Educational Psychology*, 39:8, 1047-1067, DOI: 10.1080/01443410.2019.1623382

Maxcy, S. J. (2003). Pragmatic Threads in Mixed Method Research in the Social Sciences: The Search for Multiple Modes of Inquiry and the End of the Philosophy of Formalism. In A. Tashakkori, and C. Teddlie (Eds.), *Handbook of Mixed Methods in the Social and Behavioural Sciences* (51-89). Thousand Oaks, CA: Sage.

McConnell, E. A., Birkett, M. and Mustanski, B. (2016) Families Matter: Social Support and Mental Health Trajectories Among Lesbian, Gay, Bisexual, and Transgender Youth, *Journal of Adolescent Health*, 59

McConville, J., McAleer, R., and Hahne, A. (2017). Mindfulness training for health profession students—the effect of mindfulness training on psychological well-being, learning and clinical performance of health professional students: a systematic review of randomized and non-randomized controlled trials. *Explore*, 13(1), 26-45.

McKay, J., and Devlin, M. (2016). 'Low income doesn't mean stupid and destined for failure': Challenging the deficit discourse around students from low SES backgrounds in higher education. *International Journal of Inclusive Education*, 20(4), 347-363, DOI: https://doi.org/10.1080/13603116.2015.1079273

Mero-Jaffe, I. (2011). 'Is that what I said?' Interview transcript approval by participants: an aspect of ethics in qualitative research. *International journal of qualitative methods*, 10(3), 231-247.

Michael, M., and Lupton, D. (2016). Toward a manifesto for the 'public understanding of big data.' *Public Understanding of Science*, 25(1), 104–116. https://doi.org/10.1177/0963662515609005

Mills, S. (2022). Personalized nudging. *Behavioural Public Policy*, 6(1), 150-159.

Milne, D. (2007), An empirical definition of clinical supervision. *British Journal of Clinical Psychology*, 46: 437-447. https://doi.org/10.1348/014466507X197415

Monk, Dr. E. M. (2004) Student mental health: the case studies, *Counselling Psychology Quarterly*, 17(4), 395-412, DOI: 10.1080/09515070412331331200

Mowbray, C. T., Mandiberg, J. M., Stein, C. H., Kopels, S., Curlin, C., Megivern, D. and Lett, R. (2006). Campus mental health services: Recommendations for change. *American Journal of Orthopsychiatry*, 76(2), 226-237.

Mulvenna, M., Bond, R., Grigorash, A., O'Neil, S. and Ryan, A. (2018) HILDA - A Health Interaction Log Data Analysis Workflow to Aid Understanding of Usage Patterns and Behaviours, *Proceedings AISB*

Nabeth, T.(2008) User Profiling for Attention Support at School and Work. in M. Hildebrandt and S. Gutwirth (Eds.), *Profiling the European Citizen: Cross-Disciplinary Perspectives* (1st. ed.). (185-196). Springer Publishing Company, Incorporated.

Neves, J. and Hillman, N. (2020) Stu*dent Academic Experience Survey*, https://www.hepi.ac.uk/wp-content/uploads/2020/06/The-Student-Academic-Experience-Survey-2020.pdf

Newton, J., Dooris, M., and Wills, J. (2016). Healthy universities: an example of a whole-system health-promoting setting. *Global health promotion*, 23(1), 57-65.

Northumbria University (2019) *Northumbria University to lead transformation in how the Higher Education sector identifies mental health issues in students* (Press Release accessed on 05/08/2021 at https://newsroom.northumbria.ac.uk/pressreleases/northumbria-university-to-lead-transformation-in-how-the-higher-education-sector-identifies-mental-health-issues-in-students-2882308)

O'Brien, L. S. (1998). *Traumatic events and mental health*. Cambridge University Press.

Office for Students (2018a) *Office for Students Challenge Competition Achieving a step change in mental health outcomes for all students*, 11th October 2018, online, accessed on 05/08/2021 available at https://www.officeforstudents.org.uk/publications/ofs-challenge-competition-achieving-a-step-change-in-mental-health-outcomes-for-all-students/, ref OfS 2018.41

Office for Students (2018b) *Better support, better decisions, better outcomes*, available at https://www.officeforstudents.org.uk/media/8a326ae6-b8cc-41d4-97f2-ee28a354d259/ofs-response-to-cfe-report-on-information-behaviour.pdf, accessed on 13/07/2022

Office for Students (2019) *Mental health Are all students being properly supported?,* November 2019, Retrieved March 2021 from https://www.officeforstudents.org.uk/media/b3e6669e-5337-4caa-9553-049b3e8e7803/insight-brief-mental-health-are-all-students-being-properly-supported.pdf

Office for Students (2022) *Mind the Gap: Improving student mental health support through higher education and NHS partnerships*, available at https://www.officeforstudents.org.uk/media/b3383b45-2a0b-4408-9d0c-b92c36af993c/improving-student-mental-health-support-through-higher-education-and-nhs-partnerships.pdf, accessed on 13/07.2022

Organisation for Economic Co-operation and Development, (2014). OECD guidelines on measuring subjective well-being, *OECD Publishing*. https://data.europa.eu/doi/10.1787/9789264191655-en

Pasick, R., D'onofrio, C., and Otero-Sabogal, R. (1996). Similarities and Differences Across Cultures: Questions to Inform a Third Generation for Health Promotion Research. *Health Education Quarterly*, 23(1), 142-161. https://doi.org/10.1177/109019819602301s11

Pasquale, F. (2016). Two narratives of platform capitalism. *Yale Law and Policy Review*, 35, 309-320

Patrick, B., Hisley, J., and Kempler, T. (2000). “What's Everybody So Excited About?”: The Effects of Teacher Enthusiasm on Student Intrinsic Motivation and Vitality. *The Journal Of Experimental Education*, 68(3), 217-236. https://doi.org/10.1080/00220970009600093

Pedrelli, P., Nyer, M., Yeung, A., Zulauf, C., and Wilens, T. (2015). College Students: Mental Health Problems and Treatment Considerations. *Academic psychiatry : the journal of the American Association of Directors of Psychiatric Residency Training and the Association for Academic Psychiatry*, 39(5), 503–511. https://doi.org/10.1007/s40596-014-0205-9

Peirce, C.S. (1992) *The Essential Peirce Volume 1*, edited by the Peirce Edition Project, Bloomington: Indiana University Press.

Peirce, C.S. (1999) *The Essential Peirce Volume 2*, edited by the Peirce Edition Project, Bloomington: Indiana University Press.

Peirce, C.S., (1958) Co*llected Papers of Charles Sanders Peirce*, Volumes 1–6, Charles Hartshorne and Paul Weiss (eds.), Vols. 7–8, Arthur W. Burks (ed.), Harvard University Press, Cambridge, MA, 1931–1935

Peterson, S., and Saia, T. (2022). Disability, Intersectionality, and the Experiences of Doctoral Students. *Rehabilitation Counselors and Educators Journal*, 11(1). https://doi.org/10.52017/001c.31773

Plak, S., van Klaveren, C., and Cornelisz, I. (2022). Raising student engagement using digital nudges tailored to students' motivation and perceived ability levels. *British Journal of Educational Technology.*

Poland, B. D. (1995). Transcription quality as an aspect of rigor in qualitative research. *Qualitative Inquiry*, 1(3), 290–310.

Priestley, M., Broglia, E., Hughes, G., and Spanner, L. (2021). Student Perspectives on improving mental health support Services at university. *Counselling And Psychotherapy Research*, 22(1). doi: 10.1002/capr.12391

Prinsloo, P., and Slade, S. (2015). Student privacy self-management: Implications for learning analytics. In *Proceedings of the fifth international conference on learning analytics and knowledge* (83-92).

Radhakrishnan, V., Smith, K. and O'Hara, J. (2012) The Mental Health Clustering Tool for people with severe intellectual disability, *The Psychiatrist*, 36, 454-458, doi: 10.1192/pb.bp.111.036715

Rao,U.,Hammen, C. & Daley, S. E. (1999) Continuity of depression during the transition to adulthood: a 5-year longitudinal study of young women. Journal of the American Academy of Child and Adolescent Psychiatry, 38, 908-915

Reisch, L. A., and Sunstein, C. R. (2016). Do Europeans like nudges?. *Judgment and Decision making*, 11(4), 310-325.

Reis-Filho, J. S., and Pusztai, L. (2011). Gene expression profiling in breast cancer: classification, prognostication, and prediction. *The Lancet*, 378(9805), 1812-1823.

Rimal, R., Brown, J., Mkandawire, G., Folda, L., Böse, K., and Creel, A. (2009). Audience Segmentation as a Social-Marketing Tool in Health Promotion: Use of the Risk Perception Attitude Framework in HIV Prevention in Malawi. *American Journal Of Public Health*, 99(12), 2224-2229. https://doi.org/10.2105/ajph.2008.155234

Robertson, S. L. (2018). Comparing platforms and the new value economy in the academy. In *World Yearbook of Education 2019* (169-186). Routledge.

Rockland-Miller, H.S. and Eells, G.T. (2006) The Implementation of Mental Health Clinical Triage Systems in University Health Services, *Journal of College Student Psychotherapy*, 20:4, 39-51, DOI: 10.1300/J035v20n04_05

Royal College of Psychiatrists (2021) *Mental health of higher education students*, College Report, CR231

Ruckenstein, M. and Granroth, J. (2019) Algorithms, advertising and the intimacy of surveillance, *Journal of Cultural Economy*, DOI:10.1080/17530350.2019.1574866

Sam, D. and Eide, R. (1991). Survey of mental health of foreign students. *Scandinavian Journal of Psychology*, 32(1), 22-30. doi: 10.111/j.1467-9450.1991.tb00849.x

Savolainen, L., and Ruckenstein, M. (2022). Dimensions of autonomy in human–algorithm relations. *New Media and Society*. https://doi.org/10.1177/14614448221100802

Scanlon, D. L., Rowling, l. and Weber, Z. (2007) "You Don't Have like an Identity . . . You are Just Lost in a Crowd": Forming a Student Identity in the First-Year Transition to University." *Journal of Youth Studies*. 10 (2): 223–241. doi:10.1080/ 13676260600983684

Schreiner, L. A. (2010). Thriving in community. *About Campus*, 15(4), 2-11.

Seaver, N. (2017). Algorithms as culture: Some tactics for the ethnography of algorithmic systems. *Big data and society*, 4(2), 2053951717738104.

Seifoddini, H., (1989) Single linkage versus average linkage clustering in machine cells formation applications. *Computers and Industrial Engineering*, 16(3), 419-426.

Sharp, J., and Theiler, S. (2018). A Review of Psychological Distress Among University Students: Pervasiveness, Implications and Potential Points of Intervention. *International Journal For The Advancement Of Counselling*, 40(3), 193-212. https://doi.org/10.1007/s10447-018-9321-7

Sharpe, R., Wu, Q. and Pavlakou, M. (2019) Exploring patterns of technology use in UK college students: a cluster analysis of learners' digital practices, *Research in*

Post-Compulsory Education, 24(1), 20-36, DOI: 10.1080/13596748.2019.1584436

Shobiye, L. (2022). Mothers seeking sanctuary: wellbeing, learning, and education in Wales., *Final Briefing Report*, Cardiff.

Shovon, M.H.I and Haque, M. (2012) An Approach of Improving Student's Academic Performance by using K-means clustering algorithm and Decision tree, (IJACSA) *International Journal of Advanced Computer Science and Applications*, 3(8), 146-149

Sischka, P. E., Costa, A. P., Steffgen, G., & Schmidt, A. F. (2020). The WHO-5 well-being index–validation based on item response theory and the analysis of measurement invariance across 35 countries. *Journal of Affective Disorders Reports*, *1*, 100020.

Smith, M. (2016). *One in four students suffer from mental health problems*, YouGov. Retrieved 15 May 2022, from https://yougov.co.uk/topics/lifestyle/articles-reports/2016/08/09/quarter-britains-students-are-afflicted-mental-hea

Sokal, R. and Rohlf, F. (1962) The comparison of dendrograms by objective methods. *Taxon*, 11, 33-40. doi:0.2307/1217208.

Solhaug, I., Vibe, M., Friborg, O., Sørlie, T., Tyssen, R., Bjørndal, A., and Rosenvinge, J. H. (2019). Long-term mental health effects of mindfulness training: A 4-year follow-up study. *Mindfulness*. https://doi.org/10.1007/s12671-019-01100-2 Advance online publication.

Spathis, D., Servia-Rodriguez, S., Farrahi, K., Mascolo, C., and Rentfrow, J. (2019). Sequence Multi-task Learning to Forecast Mental Wellbeing from Sparse Self-reported Data. *Proceedings Of The 25Th ACM SIGKDD International Conference On Knowledge Discovery and Data Mining*. doi: 10.1145/3292500.3330730#

Srnicek, N. (2017). *Platform capitalism*. John Wiley and Sons.

Stallman, H. M. (2012). University counselling services in Australia and New Zealand: Activities, changes, and challenges. *Australian Psycholo*gist, 47, 249 –253. doi:10.1111/j.1742-9544.2011.00023.x

Starks, T.J., Golub, S.A., Kelly, D.K., and Parsons, J.T. (2010) The Problem of "just for fun": Patterns of use situations among active club drug users, *Addictive Behaviors*, 35(12), 1067-1073.

Storrie, K., Ahern, K., and Tuckett, A. (2010). A systematic review: Students with mental health problems--a growing problem. *International journal of nursing practice,* 16(1), 1–6. https://doi.org/10.1111/j.1440-172X.2009.01813.x

Strauss, A., and Corbin, J. (1998). *Basics of qualitative research techniques*.

Student Minds (2017) *Student Voices*, available online at https://www.studentminds.org.uk/uploads/3/7/8/4/3784584/170901_student_voices_report_final.pdf, accessed on 24/07/2022

Sunstein, C (2013). Behavioural Economics and Paternalism, *Yale Law Journal*, 122(7), 1867-1899

Thaler, R. and Sunstein, C. (2008) *Nudge*, London: Penguin Books

Thomas, L. (2002) Student retention in higher education: the role of institutional habitus, *Journal of Education Policy*, 17(4), 423-442, DOI: 10.1080/02680930210140257

Thomas, L., Talbot, C., and Briggs, P. (2021). The Digital Lives of Student Mothers: A Consideration of Technologies That Support or Erode the Student/Parent Boundary. *International Journal Of Human-Computer Studies*, 154, 102689. doi: 10.1016/j.ijhcs.2021.102689

Thorley, C. (2017) Not By Degrees: Improving student mental health in the UK's Universities, *IPPR*. http://www.ippr.org/research/publications/not-by-degrees

Tinto, V. (1997) Classrooms as Communities, *The Journal of Higher Education*, 68(6), 599-623, DOI: 10.1080/00221546.1997.11779003

Tjia, J., Givens, J.L., and Shea, J.A. (2005) Factors Associated With Undertreatment of Medical Student Depression, *Journal of American College Health*, 53(5), 219-224, DOI: 10.3200/JACH.53.5.219-224

Topp, C. W., Østergaard, S. D., Søndergaard, S. and Bech, P. (2015) The WHO-5 Well-Being Index: A Systematic Review of the Literature. *Psychotherapy and Psychosomatics*; 84, 167-176. doi: 10.1159/000376585

Tressler, R. (2021) *Starting the Conversation*, UCAS Report on Mental Health available at https://www.ucas.com/file/513961/download?token=wAaKRniC, accessed on 7th July 2022

Tsai, Y. S., Whitelock-Wainwright, A., and Gašević, D. (2021). More than figures on your laptop:(Dis) trustful implementation of learning analytics. *Journal of Learning Analytics*, 8(3), 81-100.

Tsai, Y.S., Whitelock-Wainwright, A. and Gašević, D. (2020). The privacy paradox and its implications for learning analytics. In *Proceedings of the Tenth International Conference on Learning Analytics and Knowledge (LAK '20). Association for Computing Machinery*, New York, NY, USA, 230–239. https://doi.org/10.1145/3375462.3375536

Tsouros, A. D., Dowding, G., Thompson, J. and Dooris, M. (1998). Health promoting universities: concept, experience and framework for action. *Target 14 World Health Organization*. Regional Office for Europe. https://apps.who.int/iris/handle/10665/108095

Turco, R. N. (1990). Psychological profiling. *International Journal of offender therapy and comparative criminology*, 34(2), 147-154.

Unite Students, and Higher Education Policy Institute. (2019) *The New Realists: Unite Students Insight Report 2019.* https://www.unite-group.co.uk/sites/default/files/2019-09/new-realists-insight-report-2019.pdf

Universities UK. (2015) *Student mental wellbeing in higher education Good practice guide*

Universities UK. (2018) *Minding our future: Starting a conversation about the support of student mental health*, https://www.universitiesuk.ac.uk/policy-and-analysis/reports/Documents/2018/minding-our-future-starting-conversation-student-mental-health.pdf

Universities UK. (2018). Suicide-safer Universities. *Universities UK*. Retrieved March 2021, from https://www.universitiesuk.ac.uk/policy-and-analysis/reports/Documents/2018/guidance-for-sector-practitioners-on-preventing-student-suicides.PDF

Universities UK. (2020). Step Change: Mentally Healthy Universities. *Universities UK*., from https://www.universitiesuk.ac.uk/policy-and-analysis/reports/Documents/2020/uuk-stepchange-mhu.pdf accessed on 12/07/22

Van der Hof, S. and Prins, C. (2008) Personalisation and its Influence on Identities, Behaviour and Social Values. in M. Hildebrandt and S. Gutwirth (Eds.), *Profiling the European Citizen: Cross-Disciplinary Perspectives* (1st. ed.). (111-129). Springer Publishing Company, Incorporated.

Van Dijck, J. (2014) Datafication, dataism and dataveillance: big data between scientific paradigm and ideology. *Surveillance and Society*, 12 (2), 197–208.

Venville, A., Street, A., & Fossey, E. (2014). Student perspectives on disclosure of mental illness in post-compulsory education: displacing doxa. *Disability & Society*, *29*(5), 792-806.

Walker, Benjamin (2018) A Defining Moment for Personal Tutoring: Reflections on Personal Tutor Definitions and their Implications. IMPact: The University of Lincoln *Journal of Higher Education Research*, 1 (1). ISSN 2516- 7561

Walton, G. M. (2014). The new science of wise psychological interventions. *Current Directions in Psychological Science*, 23(1), 73-82.

Wamba, S. F., Akter, S., Edwards, A., Chopin, G., and Gnanzou, D. (2015). How 'big data'can make big impact: Findings from a systematic review and a longitudinal case study. *International Journal of Production Economics*, 165, 234-246.

Wang, M., Lau, C., Matsen, F. A., & Kim, Y. (2004). Personal health information management system and its application in referral management. *IEEE Transactions on Information Technology in Biomedicine*, 8(3), 287-297.

Ware, J. (1995) The Status of Health Assessment 1994, *Annual Review of Public Health*, 16(1), 327-354

Watermeyer, R., Crick, T., Knight, C. and Goodall, J. (2021) COVID-19 and digital disruption in UK universities: afflictions and affordances of emergency online migration, *Higher Education*, 81, 623–641

Watson, D. (2009) The dark side of institutional research, *Perspectives*,13(3), 71-75, DOI: 10.1080/13603100903068965

Watson, D. and Maddison, E. (2005) Managing institutional self-study (Maidenhead, McGraw-Hill/Open University Press).

Webb, E., Ashton, C. H., Kelly, P., and Kamali, F. (1998). An update on British medical students' lifestyles. *Medical education*, 32(3), 325-331.

Whitelock-Wainwright, A., Gašević, D., Tejeiro, R., Tsai, Y. S., and Bennett, K. (2019). The student expectations of learning analytics questionnaire. *Journal of computer assisted learning*, 35(5), 633-666.

Williams, M. and Dyer, W. (2004) Realism and probability In: Carter, B. and New, C. (eds) *Making Realism Work : Realist Social Theory and Empirical Research*. London: Routledge, 2004.

Williamson, B. (2019) Datafication of education: a critical approach to emerging analytics technologies and practices in Beetham, H. and Sharpe, R. (eds) 2019. *Rethinking Pedagogy for a Digital Age*, 3rd ed. London: Routledge

Williamson, B. (2019) Policy networks, performance metrics and platform markets: Charting the expanding data infrastructure of higher education, *British Journal of Educational Technology*, 50(6), 2794–2809, doi:10.1111/bjet.12849

World Health Organization. (1998). Health promotion glossary, *Division of Health Promotion, Education, and Communication.* World Health Organization https://apps.who.int/iris/handle/10665/64546

World Health Organization. (2008). *Policies and practices for mental health in Europe-meeting the challenges*. Available at https://www.euro.who.int__data/assets/pdf_file/0006/96450/E91732.pdf, accessed on 12/07/2022

World Health Organization (2021) *2013-2030 Comprehensive Mental Health Action Plan* available at https://cdn.who.int/media/docs/default-source/campaigns-and-initiatives/world-mental-health-day/2021/mental_health_action_plan_flyer_member_states.pdf?sfvrsn=b420b6f1_7anddownload=true, accessed on 24/07/2022

Xu, D., and Tian, Y. (2015). A comprehensive survey of clustering algorithms. An*nals of Data Science*, 2, 165-193.

Xu, D., Wang, H., and Su, K. (2002). Intelligent student profiling with fuzzy models. In *Proceedings of the 35th Annual Hawaii international conference on system sciences* IEEE.

Yorgason, J. B., Linville, D., and Zitzman, B. (2008). Mental health among college students: do those who need services know about and use them?. *Journal of American College Health*, 57(2), 173-182.

Zaparanuks, D., and Hauswirth, M. (2012). Algorithmic profiling. In *Proceedings of the 33rd ACM SIGPLAN conference on Programming Language Design and Implementation* (67-76).

Zarantonello, L., and Schmitt, B. H. (2010). Using the brand experience scale to profile consumers and predict consumer behaviour. *Journal of brand management*, 17(7), 532-540.

Zhou, Y.W., Zhao, L., Zhou, N.N., Zhao, Y., Marino, S., Wang, T., Sun, H.B., Toga, A.W. and Dinov, I.D. (2019) Predictive Big Data Analytics using the UK Biobank Data, *Scientific Reports*, 9, 6012, https://doi.org/10.1038/s41598-019-41634-y

Zuboff, S. (2015). Big other: surveillance capitalism and the prospects of an information civilization. *Journal of information technology*, 30(1), 75-89.

Zuriff, G. (2000). The Art of Referral in a University Mental Health Center. *Journal Of College Student Psychotherapy*, 15(1), 43-57. https://doi.org/10.1300/j035v15n01_06