From ABC's to 3P's (and a couple of T's): Exploring Factors Affecting Student Learning in Higher Education and the Need for an Updated Educational Framework.

Caroline Hands

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They say it take a village to raise a child, but in my case, it has taken a university to raise me from an unsure undergraduate student to the confident lecturer and teacher that is submitting this PhD thesis. Like most things in life, it has not been smooth or straightforward, and there were many times I did not believe I would manage to make it to the end of the process. There are not enough words, or space, to thank everyone who helped me on this journey. However, it's important to acknowledge those that have had a particularly significant role in helping me get here. This PhD would not have been possible without the care and unflagging support provided by my primary supervisor Maria, but also my secondary supervisors Ian, Minna, and John, and my independent panel members Paul and Sonia.

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Declaration

I hereby declare that this Thesis represents my original research work which has been done after registration for the degree of Doctor of Philosophy at the University of Liverpool, under the supervision of Dr Maria Limniou and Dr Ian Schermbrucker. This Thesis has not been submitted by me for the award of any other degree from any other University or Institute.

Author Contributions

Part of the Thesis has been published and part is currently under review for publication. Appendix 2 lists all the papers authored and co-authored by myself.

Studies one, two, and four of this Thesis have been published. Two in peer-reviewed international journals (studies two and four), and one in a book chapter (study one):

1. Study One: Hands, C., & Limniou, M. (2022). Why Science Qualifications Should be a Pre-Requisite for a Psychology Degree Programmes – A Case Study Analysis from a UK University. In E. Sengupta (Ed.), *High impact practices in higher education: International perspectives* (Series 51, Chapter 7). Bingley, UK: Emerald Publishing Limited.
2. Study Two: Hands, C., & Limniou, M. (2023). How does student access to a virtual learning environment (VLE) change during periods of disruption? *Journal of Higher Education Theory and Practice, 23*(2). doi:10.33423/jhetp.v23i2.5824.
3. Study Four: Hands, C., & Limniou, M. (2023). Diversity of strategies for motivation in learning (DSML) — A new measure for measuring student academic motivation. *Behavioural Sciences*, *13*(4), 301. Doi:10.3390/bs13040301.

The preliminary research results from studies one, two, three, and four have been presented at three national academic conferences:

1. Study One: Hands, C., Limniou, M., & Lyons, M. (2017). How much do subject specific A-level results contribute to first-year studies? In 14th University of Liverpool Learning and Teaching Conference, Liverpool, UK.
2. Study Two: Hands, C., Limniou, M., & Lyons, M. (2018). What can the tracking logs of a VLE tell us about student behaviours and their effects on course outcomes? In The 3rd Pedagogic Research Conference, Liverpool, UK.
3. Study Two: Hands, C., Limniou, M., & Lyons, M. (2017). Using the 'blend' effectively: Examining the value of providing online resources to students. In Association for Learning Technology, Liverpool, UK.
4. Study Three: Hands, C., & Limniou, M. (2018). Metacognitive changes across a degree. In University of Liverpool Annual Learning and Teaching Conference, Liverpool, UK.
5. Study Four: Hands, C., & Limniou, M. (2018). Updating the Motivated Strategies of Learning Questionnaire (MSLQ) for students in a digital age (DSML). In Higher Education Academy Surveys Conference 2018: Insight for Enhancement, Leeds, UK

Finally, the manuscripts of studies three and five have been submitted to high quality international journals and are currently under review:

6. Study Three: A longitudinal examination of student approaches to learning and metacognition.
7. Study Five: Expectations and reflections about starting University - a qualitative focus group study with first and third-year Psychology students.

Acronyms

Acronyms	*Definition*
BPS	British Psychological Society
BTEC	Business and Technology Education Council
CFA	Confirmatory Factor Analysis
CLT	Cognitive Load Theory
DSML	Diversity of Strategies for Motivation in Learning
EFA	Exploratory Factor Analysis
EPR	Experimental Project Recruitment
EPQ	Extended Project
GPA.	Grade Point Average
HESA	Higher Education Statistics Agency
IB	International Baccalaureate
IT	Information Technology
KMO	Kaiser-Meyer-Olkin measure
LMS	Learning Management Systems
LSI	Learning Style Inventory
MCAR	Missing Completely at Random
MAI	Metacognitive Awareness Inventory
MSLQ	Motivated Strategies for Learning Questionnaire
NVQ	National Vocational Qualifications
RSPQ	Revised Two Factor Study Process Questionnaire
SAL	Student Approaches to Learning
SAT	Scholastic Aptitude Test
SE	Self-efficacy
SRL	Self-regulated Learning
STEM	Science, Technology, Engineering, and Mathematics
UCAS	Universities and Colleges Admissions Service
ULS	Unweighted Least Squares regression
VLE	Virtual Learning Environment
WB	Welsh Baccalaureate

Abstract

Higher education is a challenging landscape to investigate, as it encompasses a diverse range of student backgrounds and requires a focus on developing metacognitive thinking skills, creating effective learning environments, and promoting student engagement and motivation. Over the years, various frameworks have been developed to describe the learning experiences and processes of higher education students. However, the rapidly changing nature of the 21st century demands that educational researchers and universities re-evaluate the established teaching and learning frameworks. This has become especially clear during the COVID-19 pandemic, where the sudden shift to online learning has highlighted the need for flexible and adaptable approaches to education. As we move forward, it is essential to continue to examine and develop effective frameworks that can support students in navigating the challenges of higher education and beyond. Three of the studies presented as part of this PhD have been published as journal papers or book chapters, while the other two are under review. In addition to the main chapter publications, several other publications have been submitted to various international journals evaluating current frameworks and providing suggestions for alternative interventions.

This PhD aims to explore several factors that influence student learning promoting a revision to the well-established educational framework of Biggs' (1993) 3P model. Despite its age this model continues to be widely used in higher education, emphasising the importance of three factors: presage, process, and product when considering the factors that affect student outcomes. The aim and the rationale of this PhD, along with a broader discussion on the widely used Higher Education frameworks are presented in the introduction, while an adapted model (3P2T) is proposed in the discussion. Each of the studies presented is related to either one or a combination of Biggs' (1993) three factors affecting student outcomes.

Specifically, study one explores the impact of prior learning and knowledge on student academic performance. This study explored the effects of prior knowledge on first-year Psychology students' academic achievements through ordinal regressions and correlations. In order to explore the role of digital learning tools in Higher Education and their potential benefits during disruptive events for learning (i.e., industrial strikes), study two compares students' Virtual Learning Environment (VLE) behaviour across three consecutive first-year undergraduate Psychology cohorts, in which one year was impacted by industrial strikes. Next, study three, empirically explores the relationship between students' learning approaches, metacognition, and academic performance using longitudinally collected data. Results suggest that a further investigation of these and other factors affecting student outcomes should be explored. Study four does exactly this and presents a new questionnaire, adapting items from the widely used Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich et al., 1991) including three new key themes of course utility, procrastination, and use of diverse sources and test anxiety. Finally, the last study, study five, qualitatively explores the multiple transitions that students undergo as they move from secondary to tertiary education (University), including changes in education, student socialisation, and emotions. Students arrive with expectations about their University experience, based on their understanding of what it means to study at this level, and the interviews explore how these expectations manifest and change throughout their degree. The study used thematic analysis to identify

five key themes that shape students' experiences: prior experience, adjustment to university, staff relationships, the experience of studying, and future plans.

Overall, the five studies employed various qualitative, quantitative, and analytical research methods in order to investigate how current Higher Education changes may affect student learning experience across different stages over their degree. The main findings of this research project argue that the need of an updated version of well-established educational frameworks (i.e., Biggs' 1993 3P model) is necessary. Such necessity is driven by the changes in University learning processes, student expectations and engagement, use of learning technologies, and the demographic pool now entering Higher Education. The research findings suggest that educational policymakers and University teachers should consider factors such as digital learning tools, diverse populations, and new teaching and learning methodologies to ensure the continuation of educational framework relevance and usefulness. Applying this consideration will guide the design and delivery of Higher Education, allowing teachers to tailor their approaches to meet the needs of ever growing and diversifying range of students.

1. Introduction and Literature Review

1.1. Overview

The life of a university student is complex. A student must juggle often-conflicting priorities associated with their current academic, family, social, and paid employment responsibilities to complete their university studies successfully while maintaining a lifestyle that satisfies their personal and social needs (Matus-Grossman & Gooden, 2002; Cheng & Alcàntara, 2007; Mills, 2020; Mills et al., 2020). Students enrol, stay, and drop out of university programs for a variety reasons, including but not limited to, personal interest, career aspiration, and skill development (Batchelor, 2006; Briggs, 2006; Balloo et al., 2015; Reed et al., 2015; Zepke, 2006). Amidst this complexity is the constantly shifting landscape of higher education, which has undergone recent significant changes due to a range of transformative factors such as the rise in virtual learning, personalised learning, independent learning, the usage of learning analytics, and the emphasis on diversity, equity, and inclusion (Li & Wong, 2020; Bonfield et al., 2020; Farrell et al., 2022; Hashim et al., 2022). Consequently, such factors have led to i) changes in to the organisational structure and management of institutions, ii) greater breadth and depth of academic programs to cater to the needs and experiences of a more varied student population, including mature (Tilley, 2014), disabled (Kilpatrick et al., 2017), international (Chilvers, 2016; Ecochard & Fotheringham, 2017), and lower socio-economic students (Devlin et al., 2012; Yorke & Thomas, 2010), as well as those with carers' vocations (Sempik & Becker, 2013). And lastly, iii) the usage of novel and digitalized teaching, delivery, and assessments. The effects of these factors were further magnified due to the recent COVID-19 pandemic (Garcia-Morales, Garrido-Moreno & Martin-Rojas, 2022).

In light of the fast-paced evolution of the higher education landscape and the diversity of students it serves, it is crucial to reassess the elements, systems, and frameworks that shape it, and to ensure that they remain pertinent and efficient in meeting the requirements of modern-day students and educational establishment. Re-evaluation and updating necessary protocols will help to ensure that the constructs used to measure and evaluate the effectiveness of higher education programs remain current and applicable within its ever-evolving landscape. There has also been a growing emphasis on employability and digital capabilities, with universities and colleges developing programmes and initiatives to equip students with the skills and knowledge required to thrive in the workplace (Jackson, 2019).

Since the higher education sector has changed markedly with respect to factors such as pedagogical methods and approaches, the use of technology, and assessment processes (Lodge et al., 2018), it is necessary to investigate whether our traditional understanding of the factors affecting students learning and academic success. This introduction will cover several factors which affect student outcomes such as technology, learning approach, student individual characteristics, and consider how these relate to a well-established model, that of Biggs 3P model (1993). This model focuses on the interplay between the student's individual characteristics, learning processes, and outcomes. Given the changes to education discussed above, this thesis seeks to re-evaluate the model and assess its continuing validity in understanding the factors affecting student outcomes.

In recent years, there has been a noticeable emphasis on adopting student-centred approaches to teaching and learning in higher education institutions across the United

Kingdom (UK). This shift marks a departure from the traditional lecture-based teaching model towards more interactive and collaborative learning methods that place students at the centre of the learning process. This change has been motivated by the realisation that students learn more effectively when they are actively engaged in their learning processes by applying their knowledge to real-world problems or seeing utility value in the material with their own lives (Hulleman et al., 2010). This shift is also in line with contemporary educational theories that highlight the importance of learner autonomy, engagement, and interaction in the learning process (Hands & Limniou, 2022; Limniou et al., 2021; Hands & Limniou, 2023). By creating a more interactive and collaborative digital learning environment, higher education institutions can better equip students with the skills they need to succeed in today's rapidly changing vocational and economic sectors (Haleem et al., 2022). Therefore, it is essential to examine some of the overarching factors that can affect all students. The thesis argues that there is a pressing need to understand the relationship between individual student characteristics, learning approaches, and academic achievement. This is because student learning is not a one-size-fits-all process; rather, it is a complex interplay between various individual and contextual factors that can impact the effectiveness of pedagogical methods. Therefore, to enhance the effectiveness of student learning and pedagogical methods, it is essential to identify and understand these factors, and how they interact with each other. When examining the complex relationship between individual student characteristics, learning approaches, and academic achievement in student learning, several models have been proposed in the educational literature. Some models focus solely on individual student characteristics, such as the Learning Style Inventory (LSI) developed by Felder and Silverman (1988). Other models, such as the Cognitive Load Theory (CLT) developed by Sweller (2010), emphasize the cognitive processes involved in learning. However, after reviewing several models, the 3P model developed by Biggs (1993) was found to be the best framework for examining this relationship. The 3P model is useful in understanding the complex relationship between individual student characteristics, learning approaches, and academic achievement. It highlights the importance of considering multiple factors when designing pedagogical methods and evaluating their effectiveness.

1.2. Conceptual Models: Biggs 3P Model

The Biggs 3P model is a framework that was developed by John Biggs and Kevin Collis in 1982 to design and evaluate teaching and learning programs. The model consists of three main components, originally Product-Process-Person, which in 1993 was amended to Presage-Process-Product (Figure 1).

This framework consists of three key components:

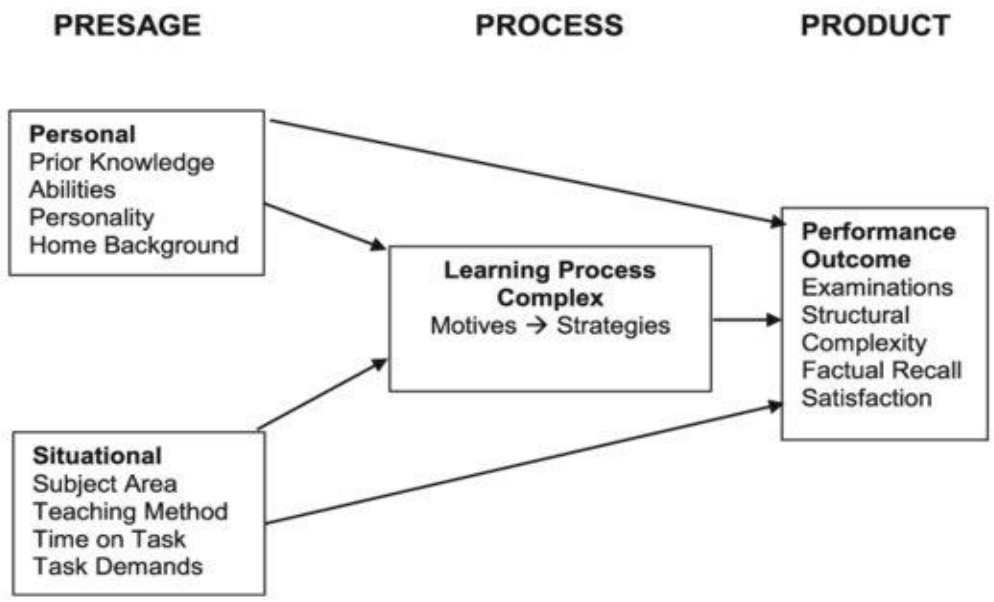
Presage: The individual factors influencing students' ability to learn. This includes both contextual and personal factors including the student's background, prior knowledge, as well as cognitive abilities, learning styles, and motivation.

Process: The learning activities and strategies used by the student and their instructors. This includes elements such as instructional design, teaching methods, and feedback provided to the student.

Product: The student's learning outcomes and achievements. This includes elements such as grades, test scores, and other measures of academic success, it can also include a lack of progress in terms of failure or dropout.

Presage factors include situational and personal student characteristics such as personality, IQ, and home background. At the centre of the model is the process level, where the learning approach taken by the student is converted into learning strategies, which in turn inform expected academic outcomes. Learning outcomes are the product of the presage and process variables and can be described quantitatively, qualitatively, and institutionally (Biggs, 1993; Hamilton & Tee, 2009; Chatti et al., 2010; Quinlan, 2019). It is important to note here that highly directive teaching may lead to factually specific outcomes. The 3P model emphasizes the importance of aligning the product, process, and person to optimize student learning. This framework is widely used in higher education and teacher education as it provides a useful guide for designing and evaluating teaching and learning programs. By using this model, educators can ensure that their teaching methods, assessment techniques, and resources align with the intended learning outcomes and the characteristics of their students, thus enhancing the constructive alignment (i.e., the effectiveness) of the program (Biggs, 1996; Kandlbinder, 2014).

Figure 1
Bigg's 3P Model



Source. Biggs (1985)

As learning involves the interaction of various individual and contextual factors, the 3P model provides a useful framework for understanding these complexities and interactions between teaching and learning elements. For example, according to Richardson et al., (1987), learning can be viewed as the interaction of individual student characteristics, learning processes, the teaching environment, and learning outcomes. Kember et al., (2004) further explain that student characteristics such as prior knowledge, ability, and preferred learning approaches interact with the teaching context (i.e., the nature of the content, the methods of teaching and assessment, the institutional climate, and the teaching procedures) to determine the ongoing approach taken by students to a particular task. The perceptions of the learning environment, as explained by Gulikers et al., (2006), can directly or indirectly influence

learning outcomes through the student's study approach. Biggs (2001) argues that each learning approach consists of two subscales - assessing intention (motivation) and evaluating strategy. Conversely, other educational theorists such as Entwistle (2011) define learning approaches (i.e., self-regulated learning) through a composite of several scales which inform and illustrate a student's quality of learning and thus their educational outcomes.

For example, self-regulated learning is viewed as a process that is not a stable trait of individuals, but rather a set of processes, including cognitive, metacognitive, behavioural, motivational, and emotional/affective aspects of learning, that are adopted and changed during learning (Panadero, 2017). As Biggs (2001) argues that this is because self-regulated learning involves the coordination of motive-strategy packages that are only applicable in the context of learning. In other words, the way a person approaches learning and the strategies they employ to regulate their own learning are influenced by their motivations and goals. For instance, a student who is highly motivated to learn a particular subject may use different strategies than a student who is less motivated. Similarly, the strategies used by a student who is seeking to master a topic may differ from those used by a student who is simply aiming to pass an exam.

When assessing learning practices, it is crucial to acknowledge that instructional approaches that work for some students may not be effective for others, as students' perceptions of teaching quality are influenced by their individual learning styles (Kember et al., 2004). Moreover, Entwistle et al., (2002) challenge the common assumption that all successful students follow the same path to academic achievement. Therefore, it is important to recognise that there is no single approach to education (or indeed to any other complex human system) that can be universally applied to meet every goal of every student (van Merrienboer & Kirschner, 2007; 2019).

Overall, factors affecting student learning are complex and difficult to define, making it essential to consider them from multiple perspectives to help gain a complete understanding of their workings and intricacies. While useful Biggs' 3P model was developed in the 1990s and since then there have been significant changes in the educational landscape including but not limited to increasing use of digital technologies, diversity of student body in cultural, socio-economic and demographic factors. At the time of development, the 3P model was designed for classroom-based highly structured higher education context and as such does not fully account for the diverse range of learners and learning environments that exist today. This PhD thesis seeks to extend Biggs' (1993) existing 3P model of learning, testing their relevance in the current education system whilst considering the current digital transformation in Higher Education. Additionally, this research aims to develop a new model that considers various contextual and personal factors which may interplay with predicting students' academic success (or failures). By doing so, this study will provide a comprehensive understanding of the complex dynamics of student learning in the contemporary educational setting. Overall, an update to Biggs' (1993) 3P model is necessary to ensure that it remains relevant and useful in today's rapidly changing education landscape. By considering the impact of digital transformation, diverse learner contexts, and emerging research findings, an updated model can provide educators with a more nuanced and effective framework for supporting student learning.

Therefore this PhD seeks to answer the following overarching questions:

How has the digital transformation of higher education impacted the relevance and applicability of the Biggs 3P model in understanding factors affecting student outcomes?

What are the most important contextual and personal factors that interact with the Biggs 3P model to predict students' academic success in the contemporary educational setting?

How can an updated version of the Biggs 3P model, incorporating the influence of digital transformation and diverse learner contexts, provide a more effective framework for supporting student learning in today's rapidly changing education landscape?

1.3. PhD Overview

This PhD study aims to understand the interrelationships between factors contributing to students' academic output, be it success or failure. The study will consist of five different studies, each examining a specific aspect of student learning. By combing the findings of these five studies, the aim is to update and expand the model suggested by Biggs (1993) facilitate the creation of a new model. Table 1 illustrates how each of the PhD studies is connected to each of Biggs' (1993) 3P categories. This research and PhD work was conducted through the Department of Psychology of the University of Liverpool.

Table 1

The correspondence of each study to Bigg's (1993) 3P Factors

Number	Description	Biggs' 3P Factors
1	The effects of prior learning (A-levels)	Presage and personal
2	The use of a VLE, during a period of disruption caused industrial action	Presage and situational
3	Student learning approach and metacognition	Presage and process
4	Diversity of strategies for motivation in learning measure (DSML)	Process and product
5	Expectations and reflections on university experience (qualitative study with students just starting or close to ending their degree program)	Presage, process, and product

The first study will focus on exploring how the presage and personal factors of prior knowledge specifically influences students' learning processes. This study will seek to identify the impact of students' prior knowledge on their ability to learn and understand new material. This study examines the importance of science qualifications to those studying within a Psychology degree program and considers the role of scientific literacy in preparing students for degree-level study. The findings of this study will help to develop strategies to ensure that degree-level Psychology students hold the relevant knowledge needed to facilitate their academic

success. It will argue that while “hard sciences”, chiefly Biology, are not the principal topic studied by Psychology students, it should be considered as a key entry requirement.

The second study will examine the presage and situational impact of VLEs on students' learning experiences and academic performance. By understanding the use and impact of VLEs on students' learning outcomes during periods of disruption this study will suggest ways of enhancing the use of VLEs to improve students' academic performance both during normal and disrupted (i.e., strikes or the recent pandemic) teaching periods. The findings of this study will contribute to the growing body of research on the use of technology and digital materials within the teaching environment, informing educators on how to best respond to teaching disruptions.

The third study encompasses presage and process factors and will focus on assessing the variation and longitudinal changes in student metacognition and learning approaches. By examining the relationship between metacognition, learning approach, and academic performance over time, this study will provide valuable insights into the factors that contribute to ultimate academic success or failure. The findings of this study will therefore help to develop strategies to enhance metacognitive awareness and promote deep learning approaches that improve students' academic performance. Furthermore, the study will provide a better understanding of how these factors change over time, which can inform the development of interventions to support students throughout their academic journey.

The fourth study looks at processes and products. It will seek to identify the most important factors contributing to students' engagement and motivation in the learning process and how such factors might help predict academic performance. By understanding the relationship between engagement, motivation, and academic performance, this study will develop a new inventory to measure study engagement and motivation. The findings of this study will contribute to the development of effective teaching and learning practices and help identify students who may be at risk of failure or disengagement from their studies.

Finally, the fifth study encompasses the whole of Biggs’ (1993) model and will examine the factors that students deem important in their studies through a qualitative lens. Speaking to students who have just completed their transition to university and to those close to their degree completion brings together the various Prestige-Process-Product elements of Biggs’ (1993) model. The findings from this study help manage the expectations of new students and address some of the difficulties associated with a smooth transition into higher education such as missing prior knowledge, independent learning with learning technologies, and how to effectively manage learning through developing good metacognitive and self-regulatory skills.

The five studies can be grouped together based on their interconnectedness, forming a cohesive body of research that gradually expands our understanding of the following factors influencing student academic performance and experiences in higher education.

Transition and Experiences in Higher Education: Study One considers the influence of prior knowledge on students' learning approaches, whilst study Five delves into the qualitative exploration of students’ transitions from secondary to tertiary education (University). Better understanding these transitional factors helps pinpoint factors central to students’ experiences and connect this to their outcomes both through direct and indirect effects. This awareness provides a solid foundation for developing an understanding of the connection

between prior knowledge and learning approaches. By recognising these transitional factors, we can develop a more comprehensive understanding of the connection between prior knowledge and learning approaches.

Understanding Prior Knowledge and Learning Approaches: Study One and Study Three are interconnected in their exploration of factors influencing student academic performance. Study One lays the groundwork by examining the impact of prior knowledge, while Study Three builds upon this by empirically examining the relationship between students' learning approaches, metacognition, and academic performance over time. Study Three considers how students' learning approaches and metacognition, which are affected by their prior knowledge, contribute to their academic outcomes. This expands our understanding of how various factors interact to influence student performance. Furthermore, it expands the understanding of how students' approaches to learning contribute to their academic outcomes. Study Two connects to this cluster by exploring how these learning approaches are moderated by periods of disruption and considers how these actions are affected by the role of digital tools in education.

Exploring the Role of Digital Learning Tools: Study Four presents a new questionnaire that includes themes like course utility, procrastination, and the use of diverse sources, all of which are facilitated by digital learning tools. These themes were not available when the original Motivated Strategies for Learning Questionnaire (MSLQ) was developed hence the need for a new measure. These digital learning tools play a large role in contributing to the various factors that affect student outcomes and processes.

Factors Affecting Student Outcomes and Performance: Overall the PhD examines how various factors affect outcomes and performance. Study One and Study Five explore the role of previous experiences and learning on students transitioning into education. Building from this foundation Study Three examines how within their studies students' learning approaches and levels of metacognition directly contribute to their academic outcomes. Study Four further broadens this exploration by presenting a new questionnaire that examines additional key factors such as self-efficacy and self-regulation shown to also affect outcomes. Finally Study Two explores how some factors change over time and due to the impact of external factors such as disruption caused by strike action.

Overall, the studies collectively examine a wide range of factors that contribute to student outcomes and performance. They progress from exploring the influence of prior knowledge to examining learning approaches, metacognition, digital learning tools, and additional factors such as self-efficacy and self-regulation. Furthermore, Study Two considers the impact of external factors on these factors over time, specifically disruptions caused by strike actions. By connecting these different aspects, the studies provide a comprehensive understanding of the multifaceted nature of student academic performance. The interconnectedness of these studies help us develop a holistic view of the factors influencing student outcomes in higher education. They contribute to our understanding of the complex interplay between prior knowledge, learning approaches, digital tools, external disruptions, and transitions, ultimately informing efforts to enhance student success and educational practices. Each study builds upon the previous one, forming a cohesive body of research, progressing from investigating the impact of prior knowledge to exploring the role of digital learning tools,

learning approaches, additional factors affecting student outcomes, and finally to the broader experiences and transitions students undergo during their university journey.

1.4. Literature Review

Each of the studies has its own literature presented in separate chapters however, a brief overview of the main topics relating to the overarching factors is presented below. The following literature review is centered around Biggs' (1993) 3P factor framework.

1.4.1. Transition to University

One of the presage factors identified by Biggs (1993) was that of the transition to university. This is assessed in Study 1, discussing the role of prior knowledge and in study five which looks at students' early university experiences through a qualitative lens. The transition to university can be impacted by various factors, including cultural backgrounds, prior learning experiences, and exposure to different teaching styles (Worsley et al., 2021; Thompson et al., 2021; McMillan, 2013). The transition itself is characterised by changes in the learning environment, such as reduced structured class time, and greater reliance on self-regulated learning (Lui & Zhang, 2023; Blackmore et al., 2021; Vosniadou, 2020). To successfully adapt to these changes, students need to understand what is expected of them and develop a meaningful connection with their university, alongside feeling a sense of belonging, and developing effective study skills (Kitching & Hulme, 2013; Richardson et al., 2012; Palmer et al., 2009). This transition from pre-tertiary education to undergraduate-level learning can be challenging for students (Parker et al., 2017). To successfully navigate the new academic demands and learning environments, targeted support and resources as well as innovative teaching and learning programs that scaffold and support independent learning are necessary. For example, Cai et al., (2015) identified themes related to the content, assessment style, and approaches to learning, and indicated the need for tailored support for students on the autistic spectrum.

During their transition, students may initially judge their efforts as sufficient, based on their own prior experiences. However, as their frame of reference shifts after some months at university, they may rate their efforts as inadequate, leading to a seeming decrease in their performance, despite these initial increases (Griese et al., 2015). It is crucial to recognise and address this phenomenon in order to provide students with appropriate support and resources to adjust to the new academic demands and learning environment (Jones et al., 2021). As discussed in Study Three, support examples include the understanding and activation of metacognition and the appropriate applications of deep and surface learning approaches.

Alongside adjusting to new academic demands, students may also encounter knowledge gaps in their field of study that can hinder their academic success. For instance, students may not expect to encounter statistics within their degree course indicating a potential knowledge gap that may impact performance (Kitching & Hulme, 2013). Moreover, students may also encounter new concepts such as Biopsychology and Cognitive Psychology, which can be overwhelming without the appropriate support (Black & Mehta, 2012).

1.4.2. Prior Learning - The Role of Previous Qualifications

One of the key areas regarding student transitions into higher education is prior learning as discussed in Studies One and Five of this thesis. The role of prior learning in predicting performance at university is complex. For example, Houston et al., (2007) found that UK students' entry qualifications did not predict first year performance at university. Similarly, Betts et al., (2008) reported that overall entry qualifications were a weak predictor of students' third year performance and overall degree classification. Furthermore, only 66% of undergraduate students felt that their A-level studies had prepared them well or very well for university learning. Among lecturers, these numbers are even lower with only 10% believing that A-levels prepared students for further study (Black & Mehta, 2012).

Some studies suggest that A-level qualifications in Psychology can make the transition to university easier for students, whilst other research refutes this claim. In their study, Forbes and Thomson (2006) reported that having a A-level Psychology qualification made the first year of university easier for 95% of their sampled students holding such a qualification. Conversely, 67% of students who had no previous experience in Psychology reported feeling disadvantaged compared to their peers with prior experience. Additionally, Rowley et al., (2010) found marked individual differences in how well students felt having a Psychology A-level qualification prepared them for university level research methods classes. Huws et al., (2005) found no significant difference between the grades of students who had studied Psychology previously to those who had not by the end of their first and second year, nor with their final degree grade - a finding echoed by the research presented in Study 1.

Prior performance has been found to be a stable predictor of future performance, with performance seen as the combination of previous effort and ability attribution (Zuffiiano et al., 2013; Gagne & St Pere, 2001). Student's transition to undergraduate-level learning from pre-tertiary education is affected by factors such as self-esteem, social support, stress, attendance, and taking a pre-university gap year (Bich & Miller, 2007b; Pownall et al., 2021; Friedlander et al., 2007). Student performance is also related to the generation and acquisition of knowledge, which Perkins (2008) categorises into possessive knowledge (the accumulation of bits of knowledge), performative knowledge (the focus on grades over engagement), and proactive knowledge (active engagement leading to personal satisfaction). It is performative knowledge and the passive displays of learning that remains a concern in this area, with many students sitting passively in large lecture halls that encourage fact memorisation and anonymity (Stefanou in Salisbury-Glennon, 2002).

The role of prior learning and scientific literacy is explored in study one which looks at the role of prior learning in terms of how well students' A-level grades prepared them for their university studies (Hands & Limniou 2023). Alongside differences in students' prior knowledge of Psychology, variation is also seen across students' level of technological capability and aptitude, with many not being "digital natives" Prensky (2009).

1.4.3. Learning Technology and Blended Learning

Learning technology has increasingly played an important role in UK higher education over the last 25 years. These technologies include the use of online learning platforms, digital resources, and multimedia tools to enhance the learning experience for students. The use of technology has also facilitated the delivery of distance-learning programmes which have become increasingly popular over the last decade and were essential during the recent

pandemic (Hodges et al., 2020; Limniou et al., 2021). A review of the literature on students' technology use shows a significant discrepancy between the confidence in usage claims and the actual evidence supporting these (Bennet et al., 2008). Despite the assumption that all students possess effective knowledge of learning technologies, Ellis et al., (2013) noted that not all students know how to use these technologies effectively, and indeed some may not find them helpful for their learning. This suggests that for most students a mix of face-to-face and online provisions (i.e., a blend of learning methods) would be more effective (Singh et al., 2021; Namyssova et al., 2019).

Blended learning combines the effectiveness of learning technology and face-to-face pedagogy which together can provide an effective platform for students to develop their metacognition and self-efficacy, as well as enhance their self-regulation skills. With its combination of online and in-person components, blended learning can provide an environment that supports the flexibility and autonomy needed for students to develop their own learning approaches. By offering a range of resources and opportunities for student engagement, blended learning can create an environment in which students can take control of their own learning and work at their own pace. This format can help students become more self-directed and engaged in their learning process, leading to improved academic outcomes and greater success in their personal and professional lives. Research supports the idea that blended learning can facilitate the development of self-directed learning. In a study by Al-Fraihat et al., (2020) students reported that blended learning gave them greater autonomy and control over their learning experience, allowing them to take ownership of their learning process. Similarly, Singh et al., (2021) found that blended learning encouraged students to take more learning responsibility and engage more deeply with course content. By providing opportunities for students to work at their own pace and to engage with course materials in multiple ways, blended learning can create an environment that supports the development of self-directed learners. One of the main ways blended learning is facilitated in universities is through using a VLE which provides a platform for both synchronous and asynchronous learning activities.

Study Two explores the Prestige factor identified by Biggs' (1993) 3P model of situational factors, exploring time spent on task and task demands for students using a VLE. It also provides an explanation of the strategy Process factor used by students through exploring how a period of disruption to face-to-face learning (caused by industrial action) affected student learning strategies. The study uses student learning logs to establish how participants interacted with a VLE. Such environments enable the retrieval and processing of large volumes of data from every interaction among learners and different agents involved in a given course, particularly those related to learners' digital footprints, that is records of learners' interactions within the VLE (Agudo-Peregrina et al., 2015). Study two's design enables a comparison of the processes undertaken by students within the normally blended learning environment alongside one in which students only had access to online materials in the VLE. This study subsequently provides some suggestions of lessons that could be learned for other periods of disruption, such as future strikes or widespread health crisis events (Hands & Limniou, 2023).

When determining the qualities of successful online learning and overall student performance Morris et al., (2005) found that successful students engaged in online learning activities at a higher frequency and for a longer time than unsuccessful dropout students. Consequently, the quality of approaches to, and the concepts of, learning technologies may affect academic achievement (Ellis et al., 2013). In fact, Margaryan et al., (2011) report that students mainly

rely on established technologies such as mobile phones, search engines (e.g., Google), and collated information sites (e.g., Wikipedia). Since Margaryan et al's (2011) publication, an increase in reliance on social media has seen students increase in their use of technology for social networking rather than for learning purposes. Moreover, when using technology for studying students tend to view learning technologies as a means of fulfilling course requirements rather than a tool that encourages deep learning approaches and testing ideas with peers (Ellis et al., 2013). In other words, students mostly use learning technologies passively for consuming information, or for downloading lecture notes (Bullen et al., 2008), or for the transmission of content, such as access to learning resources, course announcements, and information about grades. The passive use of learning technology can have a significant impact on the regulation of cognition, which refers to the mental processes involved in controlling and managing cognitive resources during learning.

The regulation of cognition can be hard in a blended environment when compared to more traditional face-to-face environments. This is because students are more isolated in blended environments and thus are exposed to fewer learning strategies/forms. As such, students need to rely on themselves to become metacognitively aware of the effectiveness of their learning strategies, detect any weaknesses and act upon these by deciding whether to keep, stop using, or implement another strategy (Goulão & Menedez, 2015). On the other hand, blended learning can have a positive impact on students' metacognition and self-efficacy as such methods provide students with more control over their learning, which can enhance their metacognitive awareness and ability to regulate their learning processes.

Research shows student abilities are a driver for the variation seen in student preferences towards learning methods and their ultimate academic successes (Khan et al., 2019). Study Two explores this further by examining the actions and successes of students with a range of academic abilities, with findings showing high self-regulating students tend to do better when learning independently. This is also supported by Azevedo et al., (2010) who suggest learning in a blended environment requires students to engage in not only cognitive processes (e.g., adopting appropriate learning strategies and activating prior knowledge), but also metacognitive processes (e.g., self- regulated strategies), motivational processes (e.g., self-efficacy and intrinsic motivation), and affective processes (e.g., anxiety and joy). By allowing students to work at their own pace and take ownership of their learning, blended learning can improve their self-efficacy and help them develop a sense of responsibility toward their academic goals (Warren et al., 2021). Moreover, blended learning can also facilitate the development of students' self-regulation skills, which are critical for successful learning outcomes (Xu, 2023; Zimmerman, 1990; Kizilcec et al., 2017; Jansen et al., 2019).

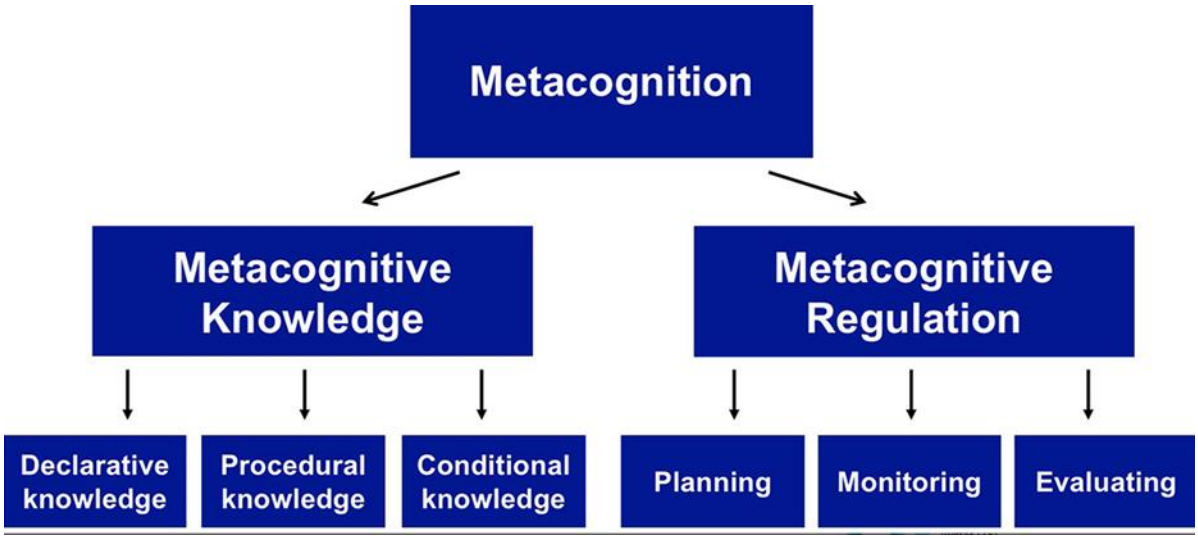
To summarise, blended learning environments often require students to set goals, monitor their progress, and adjust their learning strategies based on feedback given. These processes involve metacognitive skills such as planning, monitoring, and evaluating, which can be developed through blended learning experiences. Through these processes, students can gain a better understanding of their strengths and weaknesses and develop strategies to improve their learning outcomes. Such strategies are explored in more depth through study three which specifically examines the key process factors of metacognitive ability and its relationship with deep and surface learning approaches.

1.4.4. Metacognitive Skills

Metacognition is a term used to describe the awareness and control of mental thoughts in learning processes. According to Biggs (1993), metacognitive ability, also known as meta-learning, focuses on the processes of how to go about a task while engaging in the cognitive act of processing the learnt content. Metacognition involves the use of cognitive strategies such as planning, monitoring, and regulating one's own learning to enhance academic achievement (Pintrich et al., 1990; McCormick, 2003; Cromley & Junze, 2020). Studies have shown that when students report that they engage in multiple metacognitive approaches such as planning, monitoring, and regulating, they tend to perform better in terms of actual achievement (Pintrich & Schrauben, 1992; Garcia & Pintrich, 1996), a finding which aligns with the general assumptions of self-regulated learning (Duncan & McKeachie, 2005). As shown in Figure 2, metacognition comprises of two metacognitive components - regulation and knowledge. Research has shown metacognitive knowledge tends to be relatively fixed whereas metacognitive regulation continues to improve as students' progress through their studies.

Figure 2

Metacognition Breakdown



Despite the importance of metacognition in learning, many undergraduate students may not be aware of nor know how to utilize and customise learning strategies to leverage their maximum efficacy. In their survey, McCabe (2011) found that 80% of undergraduates reported their study strategies were improvised and not taught to them in a formal manner. Thus, educators should consider promoting metacognitive strategies and perhaps even provide formal training to enhance students' metacognitive abilities which would in turn improve their academic performance. Metacognition plays a critical role in self-regulated learning, allowing learners to be more aware of their own learning process and make necessary adjustments to improve their learning outcomes (see Winne & Azevedo, 2022; Efklides et al., 2018). By monitoring their own thinking processes, learners can identify gaps in their knowledge, identify areas where they need additional support, and develop strategies to overcome learning barriers.

Metacognitive abilities may also play a role in determining the actions that students take in terms of their learning approach and in helping them decide when “satisficing” is appropriate (Hader, 2011). Satisficing can be linked to motivation in the sense that when individuals engage in satisficing, they are trying to meet the minimum requirements to complete a task without putting in too much effort or time (Biggs, 1993). This may be driven by a lack of motivation or a (perceived) lack of ability to achieve more. A deeper understanding of the contextualized, task-specific examination of learning approaches and learning processes is necessary to fully comprehend student motivation. Motivation forms the basis of the redevelopment of the MSLQ discussed in study four. Furthermore, learning styles, which encompass an individual's preferred way of acquiring and processing information can also interact with metacognitive abilities shaping students' learning approaches and determining their inclination towards satisficing or pursuing more comprehensive learning strategies.

1.4.5. Learning Styles and Approaches

Self-directed learners are individuals who take responsibility for their own learning and are actively involved in the process of acquiring knowledge and skill development. Such students can set goals, monitor their progress, and adjust their strategies as needed to achieve their learning objectives. Self-directed learning is a process that requires a particular set of learning approaches, including goal setting, self-assessment, reflection, and metacognition. Research suggests that self-directed learners tend to use more strategic and deep learning approaches than less self-directed learners (Knowles, 1975; Spencer & Jordan, 1999; O’Shea, 2003). For example, students may engage in activities such as elaboration, reflection, and metacognitive monitoring, all of which are associated with higher levels of academic achievement (Zimmerman & Schunk, 2001; Pintrich, 2000). These learning approaches are also closely related to the development of higher order thinking skills, such as analysis, evaluation, and synthesis.

The students’ learning approach should not be viewed as a stable and unchanging psychological trait but instead as a characteristic that depends on the context within which the task is experienced (Baeten et al., 2010; Hadwin et al., 2001; Struyven et al., 2006; Winne, 2010). For example, different intentions are seen across students within their desire to understand the meaning behind a topic or simply to spot the information that needs to be learned to pass an exam. The student’s approach can also be affected by personal and situational factors, which in turn affect the quality of learning outcomes (Kanoy et al., 1989; Chin & Brown, 2000). Personal factors include ability, personality, locus of control, cognitive style, motivation, values, attitudes, prior knowledge, conceptions of learning, and general experiences, while situational factors include the nature of the task, time pressures, the context in which it is performed, the method of teaching, assessment, and perceptions of institutional requirements (Chin & Brown, 2000; Nieminen et al., 2021). Approaches to learning are therefore dynamic, malleable, and sensitive to the learner and their learning context. As a result, students adopt either deep or surface approaches, depending on their intentions.

1.4.6. Deep and Surface Learning Approaches

Deep and surface learning are two different approaches that have been widely studied in the field of education (Marton & Säljö, 1976; Dolmans et al., 2016; Øystein & Løndal., 2020; Lake & Boyd, 2015; Biggs et al., 2001). Surface learning refers to a superficial or shallow approach

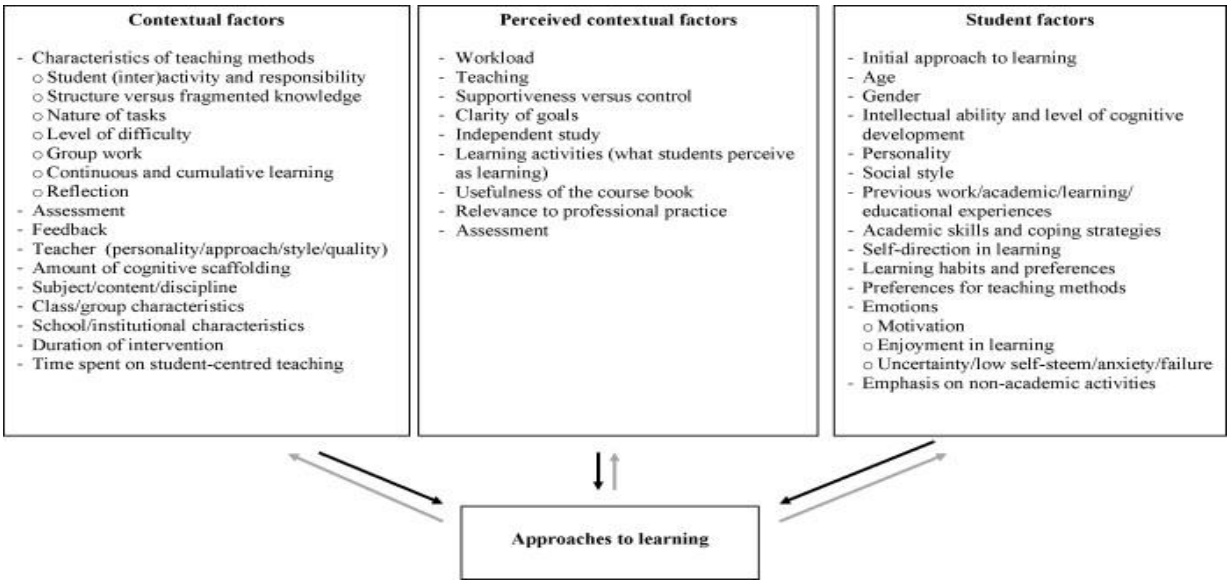
to learning, where students simply memorize information in order to pass exams or complete assignments. In contrast, deep learning involves a more meaningful and reflective approach, where students actively engage with the material in order to develop a deeper understanding of the subject matter (Trigwell et al., 2005). Surface learning is often associated with rote memorization and a focus on simply recalling information. This approach can be effective in the short term, as students may be able to immediately recall information in exams or assignments, thus performing well. However, it often results in a lack of genuine understanding, as students are not actively engaging with the material. Research has shown that students who use a surface approach to learning are more likely to experience stress, anxiety, and burnout, as they struggle to retain information and may feel overwhelmed by the amount of material they need to learn (Biggs & Tang, 2011).

In contrast, deep learning involves a more reflective and active approach to learning, where students seek to understand the underlying principles and concepts behind the material. This approach can lead to a deeper and more meaningful conceptualisation and understanding of the subject matter, as students engage with the material in a more thorough and rigorous fashion. Research has shown that students who use a deep approach to learning are more likely to enjoy their studies, have better academic outcomes, and experience less stress and anxiety (Biggs & Tang, 2011). When specifically examining the effects of student-centred learning environments on students' approaches towards deep learning, Baeten and colleagues' (2010) meta-analysis found mixed results. They concluded that the process of influencing students' approaches toward deep learning is complex, and many factors may play a role in encouraging or discouraging the adoption of a deep approach. These factors could include a range of internal and external variables such as student motivation, prior knowledge, course content, teaching styles, and cultural and societal norms. Therefore, the effectiveness of student-centred learning environments in promoting deep learning may depend on multiple interrelated factors, making it difficult to draw definitive conclusions. Baeten et al., (2010) suggest that these factors could be divided into contextual factors (and perceived contextual factors) or student factors (as outlined in Figure 3).

Students who use a deep approach to learning are more likely to engage in metacognitive thinking, as they are actively seeking to understand the material and make connections between different concepts (Pearson & Harvey, 2013). This approach involves the use of metacognitive strategies such as planning, monitoring, and evaluating one's own learning progress. For example, a student using a deep approach may set goals for their learning, monitor their progress towards those goals, and self reflect and feedback on their learning to identify areas for improvement (Lynch et al., 2010; Smith & Colby, 2010; Young, 2018). In contrast, students who use a surface approach to learning may not be as aware of their own thinking processes.

Figure 3

Baeten and colleagues (2010) Factors Affecting Student Approaches to Learning



Note. The figure shows various factors affecting students use of deep learning approaches. This highlights the bidirectional nature of approaches to learning (deep or surface) and the contextual and student factors that affect these.

These students may be less likely to use metacognitive strategies, as they are not seeking to understand the material in a meaningful way. The way in which students approach learning is closely linked to their metacognitive abilities, as students who use a deep approach to learning are more likely to engage in metacognitive thinking, which can help to support deeper understanding and long-term retention of knowledge and skills. Overall, the distinction between surface and deep learning highlights the importance of promoting active and reflective approaches to learning. By encouraging students to engage with the material in a meaningful way, educators can help foster deeper understanding and promote long-term retention of knowledge and skills.

Learning orientations are slightly wider in scope compared to learning approaches, and refer to the domain featuring students' personal goals, intentions, motives, expectations, attitudes, concerns, and doubts regarding their learning style (Vermunt & Vermetten, 2004). Rote rehearsal may be suitable for certain types of learning material or examination formats, but the surface approach often makes little use of metacognitive skills and is motivated by the students' need to avoid failure exerting a minimalist amount of effort to finish assigned tasks. The strategy of satisfying task demands by investing minimal time and effort is consistent with "satisficing" behaviours (Simon, 1955). One example of satisficing in academic learning is the strategy of rote learning, which involves memorizing content without fully understanding it. Biggs (1993) supported this idea and noted rote learning may be appropriate in certain contexts or certain tasks. Students who engage in deep learning are more likely to be

metacognitive, as they actively seek to understand the material and monitor their own understanding throughout the learning process. In contrast, surface learners may be less metacognitive, as they focus on memorizing information without actively reflecting on their own thinking or learning strategies. Study 3 seeks to explore the development of deep and surface learning in students across their degrees and considers how variations in coursework might affect this. It further explores the role of metacognition, in the longitudinal changes to students' learning approaches. The learning approach that students adopt, whether it is deep or surface, is closely connected to their motivation, as it reflects their underlying goals and attitudes towards learning.

1.4.7. Motivation

Motivation is influenced by a variety of factors, including prior experiences with subject matter, course workload, and the perceived quality of the face-to-face element in online learning environments (Nowicki et al., 2004; Kassab et al., 2015). Intrinsic motivation, which involves volitional engagement (intentional and self-directed effort) in an activity for pleasure and satisfaction, has been found to be a better predictor of academic success than extrinsic motivation (Richardson et al., 2012). Intrinsic motivation increases with age, Tilley (2014) found that mature students over 25 had a significantly higher level of intrinsic academic motivation than their younger counterparts. Intrinsic motivation also tends to increase over time - students closer to gradation show more intrinsic motivation than those who have just started their studies (Taylor et al., 2014). Context can also increase or decrease motivation in students, those who are enjoying and engaged with their learning are more likely to demonstrate motivation than those who did not (Hektner & Csikszentmihalyi, 1996; Gottfried et al., 2005). It is important to note however that a student's motivations, cognitions, and learning behaviours may vary across different classes and tasks within the same class (Credé & Phillips, 2011).

Two primary subcomponents of motivation are self-efficacy (confidence in one's ability to perform a specific task; Bandura, 2007), and epistemological beliefs (one's stance on the origin and nature of knowledge; e.g. Schraw et al., 2006). Due to being a subjective judgment, self-efficacy may not necessarily reflect the actual level of competence a student holds (Shea & Bidjerano, 2010). Furthermore, a learning situation that generates common expectations can help shape a student's motives for engaging in the task (Biggs, 1985). A student who is motivated intrinsically to learn will approach studying differently than a student who is motivated solely by fear of failure. Equally, when students display better behavioural regulation, which includes factors like intrinsic motivation, they tend to have better academic outcomes (Gillet et al., 2017).

The student's level of performance may also be influenced by their cognitive style and abilities, which affect their strategies and performance directly. Additionally, their ability to control their thoughts, motivations, behaviours, and surroundings can also impact their academic performance (Follmer & Sperling, 2016). Motivation plays a crucial role in academic success, and its lack can lead to boredom, procrastination, and poor academic performance. Motivation and self-efficacy are closely linked, as a person's level of motivation can impact their belief in their ability to successfully perform a task or achieve a goal (Wu et al., 2020). Understanding the factors that contribute to motivation, such as self-efficacy, autonomy, and interest in the task, can help educators and students develop strategies to improve motivation and avoid these negative academic outcomes. Additionally, motivation and self-regulation are

another two concepts closely linked. Research has shown that students who are highly self-regulated and motivated tend to have better academic outcomes than those who are not (Pintrich & Zusho, 2002). Additionally, self-regulated learning can actually increase student motivation, as students who feel in control of their own learning process are more likely to feel a sense of autonomy and competence, which can in turn lead to increased motivation (Ryan & Deci, 2000). Thus, fostering student motivation through the development of high levels of self-regulated learning skills is key to promoting academic success and lifelong learning.

1.4.8. Self-Regulated Learning

Self-Regulated Learning (SRL) refers to the ability of an individual to take control of their own learning process, including setting goals, managing their emotions, and using effective learning strategies. Closely related to SRL is self-efficacy which is the individual's belief in their own ability to succeed in a particular task or situation. Study Four aims to equally address and explore both concepts within the design of a new measurement tool – the Diversity of Strategies for Motivation in Learning (DSML).

In 1990, Zimmerman proposed a model of SRL comprising of metacognition, motivation, affect, and behaviour. The model aims to explain how students become active and self-directed learners through three core phases: i) forethought: setting goals, planning strategies, and anticipating obstacles; ii) performance: executing plans, self-monitoring, and adjusting strategies; and iii) reflection: reflecting on learning. SRL is composed of three dimensions, namely cognition, metacognition, and motivation, which can be further subdivided into structural and processual components (Friedrich & Mandl, 1997; Lehmann et al., 2017). Learners with stronger SRL skills tend to revisit previously studied course materials, especially course assessments, and are able to initiate metacognitive, cognitive, affective, motivational, and behavioural processes to achieve their learning goals and persist until they succeed (Kizilcec et al., 2017).

Meaningful learning is characterized by a purposeful approach in which learners constantly monitor and reflect on their learning process in order to evaluate the outcomes of their efforts. Conversely, a lack of awareness of deficient processing habits during learning can preclude the development of an understanding of the subject matter (Chin & Brown, 2000). A lack of SRL skills can also impair learning in blended learning environments (Zacharias, 2015). Self-regulation of learning is suggested to be course-specific, while self-efficacy is more likely to vary by course and discipline (Black & Deci, 2000; Chung et al., 2002). By tracking their academic achievements and failures over time, learners can become more informed about how to regulate their engagement in learning to improve the future academic outcomes. According to Winne and Nesbit (2010), as learners become more self-regulated, they tend to engage in a process of experimentation with different learning strategies and approaches, in order to enhance both their learning processes and outcomes. For instance, a self-regulated learner might experiment with different note-taking techniques or study routines to determine which strategies are most effective for them.

SRL is not a fixed trait, but rather a skill that can be developed and honed through experience and practice of applying SRL strategies (Zimmerman, 2015). It is a stable underlying structure that can take different forms depending on the subject domain. One of the key objectives of SRL research is to make predictions about students' academic achievements and, if necessary, initiate interventions to improve learning outcomes (Rotgans & Schmidt, 2009). From the SRL

perspective, agency is the capability of the individual to make and act on their selected choices. Barnard-Brak et al., (2010) argue that agency (the freedom to act) encompasses not only an individual's ability to exert their influence on the environment but also plays a crucial role in their academic achievement. In particular, individuals who develop self-regulated learning skills can take autonomous and causal actions to shape their learning experiences and outcomes.

SRL is essential for students to acquire due to its positive impact on academic achievement (Cassidy, 2011; Cleary et al., 2008; DiBenedetto & Bembenutty, 2013; Dembo & Seli, 2004). SRL demands the frequent use of active engagement, persistence in learning and refining effective study behaviours, alongside the monitoring of learning and academic achievements (Credé & Phillips, 2011; Ali, 2016). SRL has complex links, including direct and mediated effects on students' knowledge base, academic self-efficacy, and achievement (Komarraju & Nadler, 2013; Vanderstoep et al., 1996; Zimmerman, 1989, 2008; Zimmerman & Martinez-Pons, 1990).

SRL is a critical skill for success in higher education, as students must take greater responsibility for their learning and time management. The transition from secondary to tertiary education is typically characterized by a reduction in weekly structured class time, reduced direct contact with one's teachers, and a greater reliance upon SRL (Richardson et al., 2012; Broadbent, 2017). However, the impact of SRL strategies on academic performance may be different if measured at different points in the semester, as the strategies that students employ to self-regulate their learning can change over time (Broadbent, 2017). In addition to personal preferences and learning styles, the utilization preferences of individuals may also be influenced by the constraints and demands of their learning environment (Broadbent, 2017). These constraints can include factors such as time limitations, available resources, and external expectations. When considering the link to self-regulation, individuals with effective self-regulatory skills are better equipped to navigate and adapt to these constraints. Such skills allow them to make informed decisions about their learning approaches and the extent to which they engage in satisficing or employ more rigorous learning strategies. Self-regulation involves setting goals, monitoring progress, managing time effectively, and making adjustments as needed, all of which can support individuals in optimizing their learning experiences within the given environmental constraints. By understanding how utilization preferences and self-regulatory processes interact, educators and learners can work together to create environments that facilitate effective learning and enhance students' ability to regulate their own learning processes.

Self-regulation involves not only cognitive strategies, such as time and effort planning, but also metacognitive and affective strategies, including goal setting, self-evaluation, and self-reinforcement (Schunk, 2005). Cognitive strategies can include students' use of both basic and complex strategies for information-processing ranging from the basic rehearsal strategies (e.g. surface learning) through to more complex strategies such as elaboration and organisation (Duncan & McKeachie, 2005). It is important to assess self-regulated learning in a valid and reliable way to understand its relationship with academic performance. However, there is a fine line between developing a full characterization of multifaceted constructs and developing an instrument that can achieve good psychological and psychometric properties (Biggs, 1993). Students with high self-efficacy (SE), are more likely to utilize self-regulating processes such as goal setting, self-evaluation, and self-monitoring, which are essential for learning success (Zimmerman, 2000). Additionally, self-confident students tend to display greater self-control,

work harder when facing failure, prefer learning goals, and obtain better grades (Kennett & Keefer, 2006). These findings suggest a strong link between self-efficacy and self-regulated learning, where students who possess high levels of self-efficacy tend to be more persistent, hardworking, opt for difficult tasks, and manage their anxiety especially in terms of examinations.

SRL and SE are closely linked concepts in the realm of education and Psychology. Research has shown that individuals who have high levels of SE are more likely to engage in SRL, as they believe that they have the skills and resources necessary to succeed. In turn, engaging in SRL can further increase an individual's SE, as they see the positive results of their efforts and feel more confident in their abilities. Therefore, SRL and SE can have a cyclical and reinforcing relationship, each contributing to and supporting the other.

1.4.9. Self-Efficacy

The concept of SE has also been extensively studied in the field of Education. A study by Sander (2005) found that SE measures of academic confidence increase over the first year of university study for most students, including those who initially predict they are likely to perform worse than others in their group. Similarly, Goldfinch and Hughes (2007) found that students who have high initial confidence in their own self-reliance, time management, and teamwork, demonstrated better written communication skills than those together with lower initial confidence in their abilities. Meanwhile, Jiang et al., (2014) observed that student perceptions of their learning environment can affect their levels of SE, specifically, students who have a positive perception of their learning environment are more likely to have higher SE levels. SE is a multidimensional concept that centres on beliefs about future performance (Bandura, 1997). Studies have consistently shown that SE positively correlates with and robustly predicts academic performance (Honicke & Broadbent, 2016). Furthermore, SE beliefs play a causal role in the development and use of academic competencies, and may vary across domains (Bandura, 1997). Having said this, it's important to note that SE beliefs are responsive to changes in instructional experience. Kitsantas et al., (2008) found that SE became less relevant in explaining GPA by the end of the second year, suggesting that its importance may decrease over time, as more immediate factors affect student SE such as specific learning strategies, or environmental factors such as coursework deadlines.

Self-efficacious students participate more readily, work harder, persist longer, and have fewer adverse emotional reactions when they encounter difficulties than those who doubt their capabilities (Bandura, 1997). SE is likely enhanced when self-regulated learners actively manage their internal and external environment by following a scheduled timetable for study and review, clarifying intentions, determining the level of effort needed, and knowing whom to ask for help (Komarraju & Nadler, 2013). SE plays a facilitative role in relation to cognitive engagement, but cognitive engagement variables are more directly tied to actual performance (Pintrich & De Groot, 1990). Students with high SE are more likely to achieve higher grades because they are better able to control their natural impulses when studying challenging material or when they feel lazy and distracted (Komarraju et al., 2013). Finally, those with higher levels of SE are likely to select challenging tasks, persist during difficult tasks, and adapt learning strategies to more effective ones when faced with failure (Mega et al., 2014).

Levels of student SE can fluctuate throughout the semester due to continuous performance feedback. It is therefore perhaps unsurprising that Test anxiety is closely linked to SE, as students with high-anxiety may use fewer effective strategies and report less self-regulation

and persistence compared to less anxious students (Pintrich & De Groot, 1990). Equally, high levels of SE have been positively correlated with student engagement, cognitive strategies, and persistence (Pintrich & De Groot, 1990). On the other hand, test anxiety has been found to mediate the relationship between SE and other subscales of self-regulated learning (Pintrich & De Groot, 1990). Most research on emotions in education has focused on test anxiety, with few studies exploring other emotions such as shame or guilt (Trigwell et al., 2012). Studies have shown that intrinsic motivation and SE are positively related, while test anxiety is negatively related to both intrinsic motivation and SE (Stefanou et al., 2002). Interestingly, Theobald et al.'s (2022) recent study found that test anxiety hinders students' exam preparation, rather than affecting their exam performance. Students with higher test anxiety performed worse on practice questions and mock exams, resulting in less knowledge going into the final exam. However, once performance on the mock exam or practice questions was considered, test anxiety no longer predicted final exam scores. Therefore, the underlying traits of metacognition, SE, and SR all likely play a big role in equipping students with the skills to learn effectively and in turn reduce test anxiety. By examining all of these features, study four provides an effective measuring tool to identify students who are likely to be successful academically, as well as providing effective early alert for students who are at risk of disengagement, failure, and even dropout.

1.4.10. Boredom, Negative Study Habits, and Failure

Low-achieving students may lack metacognitive abilities because they tend to overestimate their knowledge (Cohen, 2012). However, research has shown that students who believe they are capable not only possess more SE but also tend to report using more cognitive and metacognitive strategies. They also have a tendency to be more self-regulating and persist more often in difficult and interesting tasks (Pintrich et al., 1990). This effect is seen regardless of their prior achievement levels, intrinsic value, or test anxiety. Therefore, it is important to explore a range of learning factors that may contribute to student outcomes. Study four discusses the development of a new measure based on the MSLQ (Pintrich et al., 1991). The new proposed measure – the DSML, has six factors measuring both presage and processes identified by Biggs (1993) and the variety of course material and learning environment as discussed by Entwistle and colleagues (2001). These factors are SE, course utility, source diversity, study strategies, test anxiety and behavioural self-regulation, which explained 22% of the model. A lack of motivation is a primary reason for student procrastination, whilst low SE and lack of interest in the task are the most significant predictors of procrastination in the literature (Steel & Klingsieck, 2016). Boredom is also linked to a lack of motivation and can lead to procrastination and poor academic performance. Research has shown that boredom in the classroom can lead to disengagement and poor academic achievement (Pekrun et al., 2011). Students who are bored may be less likely to engage with the material and more likely to procrastinate or engage in other distracting activities. Procrastination can take different forms, for example Chu and Choi (2005) identified the concept of the "active procrastinator," who employs several features to effectively achieve learning goals. Yamada et al., (2015) identified four features of active procrastination: satisfaction with outcomes, preference for time pressure, intentional decision to procrastinate, and the ability to meet deadlines. High-achieving individuals tend to use procrastination adaptively as a regulatory strategy, and the deliberate postponement of actions for utilitarian purposes, such as increasing task focus. However, Wang et al., (2015) also suggested that failure to regulate one's cognition and

behaviour should also be considered a less effective type of procrastination, that often arises from boredom.

Boredom is an emotion that can negatively impact academic performance. Pekrun et al., (2014) found that a lack of understanding and perceived relevance of lecture content can lead to low perceived control and ultimately boredom. Boredom can reduce cognitive resources, increase task-irrelevant thinking, and impair the use of effective learning strategies, leading to superficial information processing (Pekrun, 2010). Thus, it is crucial for teachers, administrators, and parents to understand whether boredom is detrimental to student performance or merely a by-product of poor achievement. Boredom can lead to disengagement with learning which in turn leads to student failure. Several factors can lead to failure in learning. Desoete et al., (2001) found that students who struggle with learning tend to attribute success and failure to external factors, hindering their effectiveness. Mäkinen et al., (2004) found a connection between non-commitment and a lack of persistence in studying. The National Audit Office (2002) identified five main reasons for student dropout, including a lack of preparedness for higher education, changing personal circumstances or interests, financial matters, the impact of paid work, and dissatisfaction with the course or institution.

These are not new issues for the pedagogic researcher, almost 50 years ago Tinto's (1975) student integration model suggested that academic and social integration into the university system was fostered by a match between the student's academic ability, motivation, and the social and academic qualities of their institution. More recently, Liz (2012) noted that students who drop out tend to be less satisfied with their university experience and may have faced issues such as isolation, concerns about future aspirations, and less engagement with peers, institutions, and staff. Students may also misattribute failures, for example Schunk (2005) found that students who perform poorly in class may attribute their poor performance to factors such as poor strategies or low motivation instead of their reduced abilities. Conversely, studies have shown that students who have higher levels of intrinsic motivation are more likely to persist in their studies, achieve higher grades, and experience more positive academic outcomes (Ryan & Deci, 2000; Vansteenkiste et al., 2009).

The factors that motivate students can vary enormously and need to be explored in great depth to truly understand this variation. As such, study five brings the PhD together by considering all of the elements examined quantitatively in the first four studies. In this study, students' experiences are explored through the lens of Biggs' (1993) 3P model across a range of topics from prior learning, transitions to university, and the longitudinal changes to students' goals, study approaches and techniques.

2. Methodology

Following the Vitae Researcher Development Framework, this PhD thesis employs various research methods across the five different studies targeted to explore the set aims and hypotheses. All five studies (and a pilot study referred to in study four) received ethical approval from the University's ethics board before data collection began. Table 2 below provides the timeline for the studies and their ethical approval numbers. While each of the studies has their own methodology section in its corresponding chapter, a brief overview is provided in this chapter.

Table 2
Chronological Data Collection and Analysis for the Five Studies

Study Number	Study Name	Ethics Number	Ethics Granted	Data Collection Timeframe	Year of Data Analysis*
1	A-Level	IPHS-396-2016	January 2015	2014 – 2019	2019 / 2020
2	VLE	IPHS-411-2016	April 2016	2016 – 2020	2021
3	MAI	IPHS-535-2016	July 2016	2016 – 2019	2022
4	DSML	IPHS-1981-2017 & IHPS10899-2021	May 2017 Revalidated February 2021	2017 – 2018	2023
5	Qualitative focus groups	IPHS-3444-2018	April 2018	May 2018	2023

* Awaiting surgery during 2019-2021 and suspended due to ill health during 2021/2022

2.1. Participants

Participants were recruited from across the University using a variety of methods such as advertising on posters and in lectures, direct email, and in-person recruitment (both in lecturers and across university social spaces). Several studies were also advertised in an internal credit scheme (the Experimental Project Recruitment; EPR), where first-year Psychology students could collect points through their participation in various experimental studies in exchange for course credit. Additionally, non-psychology participants were paid a nominal amount (£1) for their participation in the DSML study (Study Four). Table 3 illustrates the number of participants in each study.

The A-level study (Study One) and the VLE use study (Study Two) were run as opt-out studies as these were conducted using secondary student data in which students consented to share their data as part of their course participation. No students requested to opt out of the A-level study and just one student requested to opt out from the VLE study. Studies Three and Four required participants to complete questionnaire measures, while participation for Study Five was through a series of focus groups. Participants for each study were current students at the University of Liverpool studying Psychology at the undergraduate level. Study Four

additionally recruited students from across the University, because participants from various disciplines were required to test the proposed measure.

Table 3
Participant Overview for Each Study

Study Number	Study Name	Participants	Sample Number	Main Analysis Methods
1	A-level Survey and secondary data	3 cohorts of Psychology students entering between 2014-2016	1072	ANOVA, Firth logistic regression
2	VLE Secondary data drawn from student access logs	3 cohorts of 1st year Psychology students between 2016 -2018	1340	Linear regression, One-way MANOVA
3	MAI	3 cohorts of Psychology students from all three years gathered 2016/7 and 2017/8 (longitudinal data)	Time-point 1: 944 Time-point 2: 385	MANOVA, Cross lagged panel model
4	DSML	University of Liverpool students studying any course in 2018	1126	Exploratory and confirmatory factor analysis (EFA and CFA)
5	Qualitative focus groups	1st and 3rd year Psychology students from 2018	46. 14 third year and 32 first-year	Reflective thematic analysis

In most cases, demographic data was collected as well as year of study and predicted grade, as it was initially hoped to compare results across studies completed the same students. Unfortunately, while some students may have taken more than one study, there was not enough data to statically analyse these instances. Furthermore, missing data is present in most of the students' records, making it impossible to conduct inferential tests. In other words, there were not enough complete data points to draw meaningful conclusions about the relationships between the different studies.

2.2. Study Design Considerations

Studies One to Four took a quantitative design, while Study Five took a qualitative. Studies One to Three were longitudinal, Study Four was cross-sectional, and Study Five was a qualitative thematic exploration. The mixed methods approach, which is also called the multimethod use or triangulation involves utilising the strengths of each method to obtain a comprehensive understanding of the learning strategies used by different learners (Winne & Perry, 2010). This approach is considered powerful as it provides a broad and in-depth view of the learning process. Veenman and Alexander (2011) noted in their study on mixed

methods that individuals may differ in the reference points they choose, both across items and occasions, highlighting the importance of taking a multidimensional approach.

In studies One and Two, secondary data analysis was utilised with the assistance of large datasets, which allowed the researchers to draw comparisons across a whole cohort of students. The use of large datasets enabled the researchers to obtain a comprehensive understanding of the entire group's behaviour and patterns. With this approach, the researchers were able to identify common trends and patterns that may have gone unnoticed had there been smaller sample sizes. The large sample size also prevented the limitations of self-selecting non-randomised samples and allowed for broader conclusions to be drawn from the findings.

Studies Three and Four relied on self-report measures. Self-report measures are widely used in educational research to gather information about learners' thoughts, feelings, and behaviours (Schellings et al., 2011). However, as with most self-report questionnaires, respondents go through a process of comprehending prompts, recalling relevant events, filling in memory gaps, and mapping their responses to the question response scale, which can introduce inaccuracies in the data collected (Tourangeau, 2000). Additionally, there is a question of whether questionnaires measure learners' perception rather than the strategies students actually use (Winne & Perry, 2000). Despite these limitations, self-report measures have clear advantages, including the ease of administration in large-scale testing, and the fact that learners are not disturbed during their learning activities (Veenman, 2005). Therefore, researchers should carefully consider the strengths and weaknesses of self-report measures and use them judiciously in their studies.

Study Three measured metacognitive ability and learning approach. While metacognitive ability is critical to academic success, measuring it accurately can be challenging. Pintrich et al., (2000) assert that there is no single perfect tool for measuring metacognition, and research practitioners must use the instrument that best meets their goals and needs to their context of focus. The most extensively used method for measuring metacognition is the metacognitive awareness inventory (MAI; Schraw & Dennison, 1994) questionnaire, which allows participants to rate their metacognitive skills without researchers' input (Poh et al., 2016). The issue of granularity is important when considering the types of analytical approaches used to study metacognition and self-regulated learning. Converging multiple sources of data is key to developing a comprehensive understanding of the underlying metacognitive and self-regulatory process, for example using self-related measures can be correlated with actual self-regulating behaviour (Azevedo, 2009). A large part of the difficulty in measurement is because metacognition can be considered a latent variable.

Latent psychological constructs, such as motivation or self-efficacy, are often described as latent because they are not directly observed, but rather inferred from direct measurements of theoretically related variables (Lovelace & Brickman, 2013). Therefore, measuring these constructs involves using scales or questionnaires that aim to capture their underlying dimensions. However, the most important methodological concern to stress when designing and using scales to measure latent constructs is that they should not solely be a collection of questions of interest to the researcher. Instead, scales should be composed of items that have been subjected to testing for validity to show that they can serve as reasonable proxies for the underlying construct that they test (Azevedo, 2009).

Ensuring the validity of scales is crucial to accurately measure latent constructs, as measurement error can lead to biased results and incorrect conclusions about the relationships between variables. Therefore, researchers need to carefully select items for scales and establish their psychometric properties through various statistical analyses, such as exploratory and confirmatory factor analyses, to ensure that the scale items are measuring the intended latent construct (Lovelace & Brickman, 2013). In conclusion, the measurement of latent psychological constructs requires the use of scales that are composed of valid items, as they provide reliable measures of the underlying dimensions of the construct.

In Study Three participant grades were taken from academic records through students providing their student number (students were also giving the option to opt out by using a dummy number). If the researcher did not have access to student grades it was necessary to ask students to provide their grade as a self-report. While this is not as reliable as access to actual student grades, research by Noftle and Robins (2007) found a strong positive correlation between self-reported grade point average (GPA) and official GPA, suggesting that in the absence of this data, self-report offers a good proxy value, indeed when compared to overall student degree grades the distribution within the survey showed a similar pattern.

Study Four involves the development of a new measure. The rationale behind the development of inventories to address learning processes is often derived from Cognitive Psychology, specifically information processing theories. These theories are designed to address universal and culture-neutral mechanisms, making them a suitable framework for such inventories. However, when it comes to a context-dependent issue such as student learning, where student strategy is dependent on a host of factors, a top-down approach may not be sufficient. These factors include the students' values, motives, perceptions of task demand, teaching and assessment methods, and the learning environment. Thus, it is important to develop inventories that consider these contextual factors to obtain a comprehensive understanding of student learning (Biggs et al., 2001). When constructing questionnaires, there is often a dilemma between achieving good psychometric properties and providing a comprehensive representation of a complex construct. If scales are not unidimensional, reliability values tend to decrease, which presents a challenge for questionnaire designers. However, many psychological constructs are multifaceted, and a multidimensional approach would provide a more accurate representation of them. Unfortunately, commonly employed testing procedures tend to prioritize reliability over validity, which may result in an incomplete understanding of the construct being studied. Therefore, questionnaire designers must carefully balance the need for reliability with the importance of obtaining valid data that accurately reflects the complexity of the construct under investigation. In this development process, it is also important to consider trait approaches.

Trait approaches aim to assess individuals' competencies through behavioural measures and recognize the importance of cognitive, affective, and conative resources. This perspective is essential as it acknowledges the multidimensional nature of competence and the need to consider various factors in its measurement (Blömeke, 2015). Using questionnaires to derive constructs, students are typically asked about what they usually do or what they are predisposed to do, which may be one step removed from their actual behaviour in a specific task or context. Although the questions asked serve different purposes, the nature of the constructs are closely related (Biggs, 1993). Similar to many self-report questionnaires, individuals responding to the prompts go through a series of steps including understanding

the question, recalling relevant experiences, filling in any gaps in memory, and aligning their answers to the response scale. This process involves a cognitive effort on the part of the respondents, as they engage in a reflective process to provide an accurate response. By acknowledging the various steps involved in completing a self-report questionnaire, researchers can better understand the limitations of this type of data collection. Furthermore, researchers can also work towards improving the validity and reliability of the responses obtained (Tourangeau et al., 2000).

Within Study Four, once gathered the data was analysed using exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). These methods were chosen as they enable the validation of theoretical educational constructs. Commentators such as Klein (1993), and Bryman and Cramer (1997), suggest that to have a stable factor structure the sample size must be large enough to reduce correlations between factors. However, reliance on factor analysis alone to validate scales of this type is not justifiable. It is equally important to maintain the conceptual clarity of the groups of items. Therefore, the study takes both a top-down or theoretical and bottom-up data-driven approach to consider the factor structure of the amended measure.

2.3. Qualitative Study

The first four chapters of the Thesis provide a good quantitative overview through the analysis of large datasets corresponding to many of the key presage and process factors relevant to student learning. This methodology however lacks the richness obtained through qualitative methodologies. Although it may be possible to establish a connection between the presage factors and the process factors of students, which can help in explaining the variations in their end results (product outcomes). By understanding why students possess certain presage factors and how they engage in the learning process, it becomes possible to explain the differences in the outcomes they achieve. Marton (1981) argues that research into learning should prioritise the student's perspective rather than that of the teacher or academic researcher. As such, chapter five takes a broad overview of student approaches to learning directly from the student's perspective. It does this by examining the expectations of students in the first few weeks of their educational journey and contrasting this with the narratives given by students at the end of the process of gaining a degree.

Qualitative focus groups have become increasingly popular in higher education research as a method of exploring students' experiences and perceptions of various aspects of their academic journey. One such study by Drew (2001) examined the relevance and effectiveness of study skills units for first-year undergraduate students. The study found that some students did not perceive the value of such units at the time they were completing them but later reflected on their usefulness as they progressed through their studies. This highlights the importance of allowing time for reflection and considering the long-term benefits of academic support interventions. Another benefit of conducting focus groups is the opportunity to identify discrepancies between students' expectations and the realities of University resources and practices. Crisp et al., (2009) used focus groups to explore the experiences of international students at a UK University. Their study found that some students had unrealistic expectations of the resources available to them, such as assuming one-to-one tutoring would be readily available. The study also revealed that some university practices, such as group work, were not always aligned with students' cultural expectations. These findings emphasise

the need for universities to be transparent with students about available resources and to consider the diversity of student expectations and experiences.

To summarise, qualitative focus groups provide valuable insights into students' experiences and perceptions of various aspects of their academic journey. They allow for the exploration of the effectiveness of academic support interventions and the identification of areas where student expectations may not align with university practices. By incorporating student feedback and adapting to diverse student needs, universities can enhance the student experience and ultimately improve student outcomes. Study five utilises a thematic analysis approach meaning that, unlike many other qualitative approaches, it is not tied to a particular theoretical or epistemological perspective (Braun & Clark, 2006). This approach provides flexibility to cover a large variety of topics suiting the diverse base of topics found within teaching and learning. Furthermore, the study uses an inductive analysis drawn from the data itself (Maguire & Delahunt, 2017).

3. Study One: Why Science Qualifications Should be a Pre-requisite for Psychology Degree Programmes – A Case Study Analysis from a UK university

Abstract

It has been claimed that prior learning and knowledge is one of the most reliable and consistent predictors of student achievement (Richardson et al., 2012). Although for UK Higher Education the traditional A-level (advanced level qualification) remains the principal qualification students use to gain entry to university, there has been a small but significant rise in alternative qualifications, such as the International Baccalaureate (IB) and vocational qualifications such as that from the Business and Technology Education Council (BTEC). The multi-disciplinary nature of Psychology means students enter the degree programme with a range of qualifications in differing topic areas. The current case study aimed to assess if science qualifications aided student success in the University of Liverpool's Psychology course. Ordinal regression and correlations were used to examine the impact of prior qualifications on three first year cohort module scores (Psychobiology, Social Psychology, and Research Methods) and the overall degree mark across three cohorts of Psychology students (N = 1,072). University entry grades showed a significant overall and subject specific effect of scientific prior knowledge. However, the effects of previous qualifications were not cumulative and did not persist beyond the first year of study. These findings were strongest for Chemistry in the Psychobiology module suggesting that scientific literacy - the understanding of scientific concepts, phenomena, and processes, as well as an individual's ability to apply such knowledge to new or non-scientific situations (Schleicher, 2019) - rather than domain specific knowledge is driving such increase in grades. A negative relationship was seen for those holding BTEC qualifications, suggesting that vocational qualifications, specifically for this Psychology program, were of less use than academic ones, even if topic areas were similar – a finding which may also apply to other academic based courses, and warrants further study. Although the advantage of prior qualifications diminishes across the course of study, this small but distinct advantage suggests that making a science qualification a requirement for a place on a Psychology degree course would be a beneficial step for admissions tutors to consider.

Introduction

The higher education sector is currently undergoing several wide-ranging changes, such as increases in the use of technology and widening participation (Cornell-Smith & Hubble, 2018; Taylor, 2020). Internationally courses in higher education employ a variety of methods for recruiting students such as the use of school leaving certificates (an omnibus qualification), previous grade point averages (GPA), entrance exams, and prior individual qualifications. This current case study examines the situation in the United Kingdom (UK) where individual

qualifications (predominantly A-levels and GCSEs) are the primary methods used by university admissions staff to determine entry criteria. In 2017 approximately 600,000 applicants applied for an undergraduate place at a UK university (Universities and Colleges Admissions Service, UCAS, 2017). Every course programme sets specific entry requirements ensuring the skills and level of prior knowledge needed from students to successfully complete their degree of studies. With University admission numbers ever-increasing, students are entering university from progressively more diverse backgrounds, and holding a larger array of qualifications, both in type (e.g., IB, BTEC, and Welsh Baccalaureate, WB), as well as domain (e.g., mediaeval, and Norwegian studies). As such, educators must be mindful of the changing pedagogical landscape and should explore whether such diversity in skills and knowledge is beneficial for the success of their students, and, if these factors should be incorporated within entry criteria supporting contextualised admissions and improving the transition to higher education for all students.

Factors Affecting Successful Student Learning

Prior literature (e.g., Richardson et al., 2012) has explored the effects of (1) previous academic performance, (2) studential factors (i.e., self-efficacy), (3) individual characteristics (i.e., motivation), and (4) prior knowledge (knowledge gained prior to starting a current course/topic of study that is helpful or relevant to current learning). Research has shown that previous academic performance provides the basics of the topic, and repetition of this has a positive impact on student learning outcomes (Cassidy, 2012). Studential factors such as metacognitive ability (Tobias & Everson, 2009), self-regulation, and motivation (Zimmerman & Moylan, 2009) are shown to strongly influence learning outcomes. Individual characteristics such the degree of enthusiasm, learning engagement, cognitive abilities, motivation, and demographic variables like gender, age, and personally traits, (e.g., conscientiousness) have all been used to predict first year success (Bone & Reid, 2013; Ochonogor, 2011; Voyer & Voyer, 2014; Win & Miller, 2005; Olani, 2009; Naderi et al., 2009; Kuh et al., 2008). In a study with 9,000 Dutch students, Van den Berg and Hofman (2005) suggested that studential factors accounted for 95% of the unexplained variance in outcomes with just 5% due to specific course related factors such as teaching quality.

Critically, as Zeegers (2004) notes whilst there are multiple factors which may contribute to learning outcomes, very few (such as grades and the number of dropouts) have a direct and measurable effect. For those that do however, prior achievement is perhaps the most pre-eminent. For example, Sackett, Borneman, and Connelly (2008), examined a variety of psychometric measures and found a person's cognitive ability to be one of the stronger predictors of both short and long-term academic success. Further, it could be argued prior discipline knowledge can act as a proxy for cognitive ability (Lövdén, 2020), since to succeed in the qualification the student must possess the requisite abilities to do so. This is further echoed by Richardson et al's (2012) wide-ranging meta-analysis that examined multiple factors affecting student outcomes. Demographic and psychosocial contextual factors generated only small correlations with SATs (Scholastic Aptitude Test) or GPA scores, whereas medium sized correlations were found when previous knowledge was considered. Some researchers have studied the role of prior knowledge, generating theories such as Bloom's Taxonomy and creating the practice of cross curriculum teaching, whilst also exploring its effects on entry qualifications across different university courses. For example, Farley and Ramsay (1988), found that academic ability and prior knowledge were strong predictors of Mathematics performance in first year classes. Additionally, Evans and Farley (1998), found

that when it came to final year advanced Mathematics in school, achievement was significantly and positively related to university performance in Mathematically based background subjects. Equally, when examining prior knowledge in cognitive Psychology, Thompson and Zamboanga (2004), found that domain-specific prior knowledge uniquely predicted exam performance over general aptitude. Contrastingly, Schaap et al., (2012) studied the role of prior knowledge in Psychology courses, finding that while initial learning at higher levels predicted retention figures, prior knowledge did not.

Much of the previous research has centred on the effects of prior knowledge and its role in facilitating the learning of new content. Findings show that concepts such as scaffolding, repetition, and expanding on previously learned content all help students increase their learning (e.g., Dobson & Skuja, 2005; Dochy et al., 1999; Hailikari et al., 2007; Hattie, 2008; Schut et al., 1998). Additionally, several researchers have found medium to strong correlations between GPA and previous study such as SATs (Berry & Sackett, 2008), as well as secondary school grades (Power et al., 1987). Additionally, a systematic review of educational meta-analyses, found very large effect sizes (d = .90-.79) for both prior knowledge and intelligence levels, and a medium effect (d = .49) for academic achievement on both SAT and GPA scores (Schneider & Preckel, 2017). Qualitative investigations undertaken by the National Audit Office (NAO; Comptroller & General, 2002) suggested that prior academic achievement was an important predictor of academic performance and meditates the risk of student dropouts; however, not all research agrees, particularly when examining college students. For example, Mouw and Khanna (1993), found that the combination of examined predictors, including student prior knowledge, explained only around one quarter of the variance. As such, most of the variation between student's college achievement was unexplained, suggesting that prior knowledge is important, but not the only factor in academic success. Despite some variation across institutions, the main admission criteria currently used within the Higher Education sector is entry qualifications. Therefore, it is important to expand on the work of previous studies such as that of Hourigan and O'Donoghue (2007) to explore the role of entry qualifications and their relation to student prior knowledge and academic performance.

Entry Qualifications

The principal qualifications students use to gain entry to university remains the traditional A-level for all UK Higher Education, bar Scotland. A-levels are a qualification which are typically studied over two years and focus on a single subject area such as Mathematics or Geography. However, a small but significant rise has occurred in alternative qualifications. Furthermore, even the traditional A-levels may be supplemented by an extended project (EPQ) - a project which offers students the chance to explore a single topic of the student's choice in more depth thus is similar to a dissertation albeit at a lower level. Gill (2018) identified the extended project qualification as one seen to provide particularly good preparation for university study, due to its focus on degree related skills such as problem-solving, planning, and research. Furthermore, extended project students are increasingly replacing traditional A-level qualifications with other forms such as the IB or BTEC diplomas, a vocational qualification covering a broad topic area (such as computing), which is equivalent to 3 A-levels (UCAS, 2018).

BTEC qualifications are often seen as more vocationally based and aimed at students who desire a vocational pathway, or for those who experience barriers to educational engagement and attainment. Since 2013 several Russell Group Universities (a collection of 24 public

research UK Universities) actively advise students that BTEC qualifications may not be suitable for some courses. Equally in some institutions where they are accepted, a distinction grade is required (Gill, 2018). For example, Brimble (2015) examined students' pre-registration qualifications in the vocational degree of nursing and found no significant differences in attainment between A-level and BTEC students. However, other studies found that students with BTECs were less likely to gain first class degrees (Gill, 2018) and more likely to drop out (Holland & Murphy, 2016). These studies suggest that in addition to the level of qualification, prior knowledge may be valuable but context dependent, with some topics that contain vocational elements more likely to show value to vocational qualifications than those with a purely academic basis such as mathematics.

At the other end of the scale, IB has been seen by some universities as a more challenging qualification covering a range of cognitive topics within each programme. The 2011 Higher Education Statistics Agency (HESA) report suggested there was a clear relationship between performance in the IB and undergraduate students gaining first-class or upper second-class honours degrees (Gill & Rodeiro, 2014). Both the BTEC and the IB qualifications seek to cover a wider range of skills and abilities, while the domains of the specific A-levels focus on single subjects, such as Chemistry, Biology, and Mathematics.

University undergraduate courses generally cover a large amount of material across a broad subject area, potentially causing difficulties for students without prior knowledge in the relevant subjects. First year courses are often taught in large cohorts who may exhibit a wide range of knowledge and/or abilities. Such courses therefore need to offer a compromise between providing a broad base of learning with course specific knowledge to enable all students to reach a similar level by the end of the degree.

Prior Learning in the Sciences

Learning can be either domain specific, covering particular knowledge on a topic (Stemler, 2012), or it can be more generalised e.g., emphasising critical thinking skills (Rayner, 2014). Both types of learning could act as differential indicators for potential academic success. For example, new undergraduate Psychology students may start with a wide range of prior knowledge both from an academic context (prior entry qualifications) and/or learning from a more casual or informal context, such as magazine articles, or social media posts (Merchant, 2012). The effects of prior knowledge in Psychology particularly the role of entry qualifications in science topics, are yet to be fully addressed in the literature. Huws et al., (2006) examined the role of GSCE courses (qualifications taken at age 16, covering a large basis of topics, which are then built upon in A levels) on degree success finding both sciences and English predicted higher achievement at degree level, whilst A level results did not, however the entry criteria for their institution already specified a science A-Level limiting the transferability of this finding to the current study.

Furthermore, much of today's research tends to focus either on wide ranging introductory courses which can be taken by any student studying for a Higher Education degree - as is common in North American (USA and Canada) and Australian education systems. In other literature the focus is placed on studying the effects of single cognitive subjects which are often the focus of a university degree (e.g., prior knowledge in Chemistry for a Chemistry degree). It is within the gap between single topic degrees and introductory courses that

psychology sits offering a broad introduction to the topic, whilst requiring knowledge in areas such as Mathematics and the sciences.

Pertaining specifically to science courses, the effects of prior knowledge (as measured through previous academic performance) can be quite marked. McKenzie and Schweitzer (2001) examined students studying various STEM (Science, Technology, Engineering, and Mathematics) and IT (Information Technology) subjects finding that previous academic performance was one of the most significant factors predicting first year university performance. Nivala et al., (2016) investigated students' academic performance in first-year medical courses in relation to the various components of an entrance examination. In this case, only questions relating to Biology were found to significantly predict first year student performance. When examining Anatomy and Physiology undergraduate students, Anderton and Chivers (2016) found significant relationships between test results in core first year modules and previous achievement scores. Regarding the traditional high school sciences similar results have also been found for students studying for a degree in Chemistry (Clark, 2011; Simpson et al., 2012) and Biology (Binder et al., 2019; Rayner, 2014; Smiley, 2013; Tamir, 1969). Surveying 2,667 students studying for a Biology degree, Loher et al., (2012) found a significant association between previously studying Biology and the student's final grade in a first year introductory Biology course. Thus, all of the above demonstrate a connection between scientific prior learning and degree subject, however the picture is not as clear-cut as it could be.

There are many studies that present contradictory findings to the ones presented above that support the effects of prior knowledge and student academic performance. For example, when examining Biology courses, Johnson and Lawson (1998) found that reasoning ability, rather than prior biological knowledge, was the most significant predictor of final exam scores. Furthermore, Bone and Reid (2013) looked at academic performance in an introductory Biology class over three cohorts and found the prior study of Biology did not account for grade variance. In fact, prior Chemistry knowledge was the only predictor found to be beneficial, suggesting that the nature of the course may affect the usefulness of prior learning in predicting academic success. Indeed, as Rennie et al., (2001) noted "true scientific literacy" is often not an outcome of school-based science education, but rather that teaching focus is on the transmission of discrete facts within the topic, thus limiting the transferability of this learning.

These discrepancies in the literature suggest that prior knowledge is perhaps, less important if the focus of study has been overly domain or content specific, with a focus on learning the "facts". This brief review of the literature seems to suggest that those students who can develop scientific literacy, in turn enabling themselves to build on their prior knowledge from previous learnings, will be the most successful. In order to empirically study the aforementioned point McCoy and Pierce (2004) compared attainment across two cohorts. Students who held the relevant prerequisite qualifications passed at higher levels than those without the specified pre-requisites. Furthermore, among students who held the relevant prerequisites, both failure and withdrawal rates declined by around 20%. These findings suggested that such academic predictors could also be used to identify first year science students at risk of failing (O'Byrne et al., 2009 as cited in Bone & Reid, 2013).

Conversely to scientific literacy which remains helpful to students across their studies, when tested longitudinally the effects of such domain-based knowledge reduce. Examining the

effects of prior knowledge on Biology for an Osteopathic University course, Palfreyman et al., (2018) found having previous Biology knowledge confirmed a moderate advantage in first semester examinations but had no significant bearing on final first year exams. A potential explanation for this finding is that although Biology is a valuable topic for undergraduate students to understand the Osteopathic field, it is not the only required topic. Thus, the effects of prior knowledge in this context may be limited. A similar topic is that of Psychology, where skills in Mathematics and Biology are considered equally as important as prior Psychological knowledge for successful outcomes at all levels of the degree, but particularly in the first year of study.

UK University Psychology Courses

Unlike the Mathematics or Biology undergraduate courses discussed above, Psychology modules tend to cover a variety of topics and do not follow a clear path from A-level to degree. For example, the Psychobiology module offered at the researcher's institution tends to sit between Biology and Psychology, requiring knowledge of elements from both subjects. Furthermore, the research methods and statistics module also offered requires some mathematical knowledge, although this knowledge can be fairly specific and is only covered in some mathematical qualifications (Borne, 2018). In addition to this variation, exact entry qualifications for a Psychology undergraduate course vary across the UK Higher Education sector. Many universities ask for at least one science-based A-level (e.g., The University of Manchester, University College London), whilst other universities state science qualifications as a preference, but not part of the formal offer (e.g., The University of Reading, Warwick University). Uniformly, however all Russel Group Universities have similar entry requirements for their Psychology courses. Within first year modules and throughout the degree, three broad areas are covered to meet the British Psychological Society (BPS) accreditation guidelines for Psychology degrees and QAA Subject Benchmarks (the UK Higher Education quality code). These three broad areas consist of social and developmental based modules, statistically based courses such as research methods, and modules that are biologically or cognitively based (e.g., Neuroscience).

This brief literature review demonstrates that prior knowledge demonstrated by entry qualifications can play an important role in students' academic performance. Therefore, the current case study aims to assess if prior science qualifications (both academic and vocational) aided student success in the University of Liverpool's Psychology course both in first year modules and the overall degree mark.

The Current Study

The prediction of student success enables educators to tailor their courses more specifically to a cohort's needs. An introductory module that is too simplistic, or one that assumes too much prior knowledge risks boredom and disengagement with studies. Whilst the predictors of student success have been measured in other disciplines of social science, the application and investigation of specific predictors within Psychology is limited to a few studies such as those conducted by Betts et al., (2008) and Pownall et al., (2021) both of whom examined A-level grades in aggregate.

Yet to be empirically tested is the theory that suggests whilst not required for program admission, holding a science-based A-level is believed to be advantageous to students. As

such, the current study explored and analysed the effects of A-level science qualifications (or its equivalents) on three cohorts of Psychology student's academic performances, using correlations, ordinal, and frith logistic regressions. Current first year modules include i) Social Psychology which directly relates to A-level Psychology, discussing personality and individual differences; ii) Research Methods and Statistics which covers basic research methodology, as well as introducing students to statistical tests, such as the student T-test and ANOVA. Although the topic is not closely related to a particular A-level learning content, a background in maths is considered helpful for parts of this module. Lastly, iii) the Psychobiology is a broad introductory module covering the brain's structure and biological functioning, thus being at a similar level of educational content to A-level Biology. To summarise, the study will explore the three following hypotheses:

> H_1: Possessing an A-level in a traditional science topic (i.e., Biology, Chemistry, or Physics) will be an important predictor of achievement, with the final scores from the three first year Psychology modules all being higher for those with a science topic A-level compared to those without.
> H_2: Students with associated science qualifications (Psychology, Health and Social Care BTEC, or Mathematics) will perform better than those without.
> H_3: The number of science A-levels held by students will cumulatively and incrementally predict grade attainment over and above general ability/aptitude.

Method

In order to address the above hypotheses a quantitative study examining archival data records relating to student's entry qualifications and performance within the Psychology undergraduate degree programme at the University of Liverpool was undertaken. Ethical approval for this study was granted by the University of Liverpool's Ethics Committee (IPHS-201516-435).

Participants

The data was supplied by the University of Liverpool's admissions department and the School of Psychology. Overall data from 1,154 students was collected from three consecutive years (2014 – 2016). Any students who did not start the Psychology course or dropped out prior to the final examinations in their first year was excluded from the data analysis (n = 37).

Qualifications

Students entering the Psychology undergraduate course typically have an offer of ABB, (although there is some variation across birth years and within clearing). Students have a diverse array of qualifications, ranging from traditional A-levels to combined qualifications of IB, BTEC, and National Vocational Qualifications (NVQ). Aside from the traditional sciences and Psychology, 116 other subject entry qualifications were held by accepted students in the sample, encompassing both traditional (e.g., Geography, English) and non-traditional subjects (e.g., Norwegian Studies, Medieval Art), showcasing an incredibly diverse range of prior knowledge. Since this investigation is concerned with the sciences, the effects of 5 A-level qualifications - Biology, Chemistry, Physics, Mathematics, and Psychology - along with the one Health and Social Care BTEC were analysed. The Health and Social Care BTEC, which offers a basic introduction to various topics (such as public health and lifespan development) relating

to the health and social care sector was included in the analysis due to a substantial number of students entering with this qualification as well as its natural overlap with Psychology modules making it a likely candidate for aiding degree success due to this shared prior knowledge. Additionally, the cumulative effects of holding more than one science qualification were also tested.

In order to compare the numerous types of entry qualifications (IB, NVQ, and BTEC), each qualification type and grade was converted to UCAS tariff points (a standardized point system, allowing comparison between differing qualification types which is used to make entry decisions). These figures were then adjusted in line with Thompson (2013) to ensure that there was parity between the differing qualification types. Each subject qualification was measured and calculated on both an average and highest achieved point score. A small number of international qualifications, along with students whose entry came from undertaking access courses were not transferable to the UCAS point's tariff and therefore removed from the data analysis (*n* = 23).

Table 4

The distribution of entry qualifications for the three academic years of University of Liverpool Psychology students (N = 1,072)

Entry Qualification	Percentage of sample holding qualification (%)
A-level Psychology	88
A-level Biology	35
A-level Chemistry	11
A-level Physics	2.5
A-level Mathematics	16
Health and Social Care BTEC	7

Measures

Five performance measures were taken. The first three measures were the final scores from the three first year undergraduate Psychology modules - Social Psychology, Research Methods and Statistics, and Psychobiology. To further test whether any effects of A-level course prior knowledge persist across the degree course the final cumulative grade each student received at the end of second and third year (i.e., the completion of their degree) was also taken. Cumulative grades were used for these 2 measurements as students undertake differing modules in these years.

A dataset was compiled and included the Psychology entry qualifications of each undergraduate student who had enrolled and started the course between 2014-2016. This time frame was chosen due to being the period immediately before sciences were added as a prerequisite for the courses' entry, partially because of the findings arising from this study. Additionally, the scores of each student's final mark from their three first year modules and their final degree were included.

Analysis

A final total of 1,094 student entries were analysed with 332 students starting their studies in 2014, a further 420 students starting in 2015, and 342 students from the 2016 cohort. Most students (88%) had a Psychology entry qualification (see Table 4). A small number of students

held none of the 6 science qualifications of interest so were excluded from the final analysis (*n* = 22). As such, the resulting analysis used a sample of N = 1,072 students.

SPSS software was used to analyse the data. Correlations, ordinal, and logistical regressions based on student's A-level results which had been converted to the relevant UCAS tariff points. Specifically, ordinal regressions were used to examine the association between each qualification and grade outcome, whilst controlling for the other qualifications held by each student. Results from this were used to explore any cumulative effects of holding multiple qualifications, and whether any effects persisted into the second or third years of study.

Results

In order to investigate the data from each of the three student cohorts it was first necessary to establish whether they were significantly different from each other in terms of both grades and/or distribution. A one-way ANOVA showed no significant effects (F (2,1070) 6.89, *p* = .68). The distribution of final degree grades from the total sample (61.85 ± 11.15) reflects a typical grade distribution for a UK Psychology course. 23% of students achieved first-class marks, 42% achieved a 2:1 grade, 25% gained a 2:2, and 5% scored third class marks. A small proportion (around 3%) failed the course, mostly due to absence, and were given the opportunity to re-sit affected modules in the summer period, these students' original grades were included in the analysis.

Overall Mark & Qualification

When examining the data at course level, there was a small but significant positive correlation found between the overall mark for first year and the total number of science qualifications taken by the students, *(r* (1070) = 0.293, *p* = <.001). In order to investigate this relationship further, a binary ordinal regression was performed examining overall grade boundaries as an outcome, with the odds of increasing the grade boundary within the individual model as a predictor, whilst the total number of sciences was used as a covariate (N = 97). Regarding the overall scores Psychology, Biology, Mathematics, and Chemistry were all shown to have a significant effect; however, this was not cumulative, as the total number of sciences taken had no outcome effect (see Table 5). Note, the non-significant finding of the Physics entry qualification was most likely due to its small sample size. The Health and Social Care BTEC showed a significant negative relationship between each individual module outcome and overall degree score.

The data's differences can also be explored at the Individual grade outcome level. Further regressions were conducted on the grade boundaries of the three first year modules (Social Psychology, Research Methods and Statistics, and Psychobiology). Using a firth logistic regression, the likelihood of increasing one's overall grade up to the next grade boundary (e.g., the likelihood of going from a 2:1 to a first) was also examined. The results (see Table 6) produced a mixed picture, with only some entry qualifications showing significant differences. Notably, possessing a Biology qualification significantly increased the possibility of moving from 2:1 to a first-class degree, similarly, possessing a Chemistry qualification significantly increased the possibility of moving from a 2:2 to a 2:1, and possessing a BTEC in Health and Social Care had a significant negative effect on the probability of gaining a first-class degree.

Table 5

Ordinal Regressions by Module Grades

	Overall (*n* = 1072*)*	Social Psychology (*n* = 967)	Research Methods *(n* = 1074)	Psychobiology *(n* = 1060)
Data Fit	χ^2 = 114.42, *p* <.001	χ^2= 70.61, *p* <.001	χ^2= 74.83, *p* <.001	χ^2= 125.45, *p* <.001
Pearson Nagelkerke	r = .80	r = .44	r = .41	r = .68
	R_n^2 = .121	R_n^2 = .096	R_n^2 = .074	R_n^2 = .117
Psychology	OR = 1.61 (1.09 ~ 2.39)	OR = 1.60 (1.09 ~ 2.40)	OR = 1.53 (1.04 ~ 2.15)	OR = -0.38 (-0.72 ~ -0.37)**
Biology	OR = 1.64 (1.16 ~ 2.33)	OR = 1.47 (1.09 ~ 1.87)	OR = 1.40 (1.06 ~ 1.86)	OR = 1.51(1.01 ~ 2.64)
Chemistry	OR = 1.66 (1.08 ~ 2.53)	OR = 1.65 (1.08 ~ 2.52)	OR = 0.48 (-0.06 ~ 1.02)**	OR = 1.73 (1.26 ~ 2.40)
Mathematics	OR = 1.57 (1.09 ~ 2.25)	OR = 1.56 (1.08 ~ 2.26)	OR = 1.73 (1.14 ~ 2.64)	OR = -.24 (-0.59 ~ -0.11)**
Health and Social care BTEC	OR = -0.81 (-1.24 ~ -0.36)*	OR = -0.90 (-1.42 ~ -0.39)*	OR =-2.49 (-0.68 ~ 0.18)*	OR = -0.81 (-1.24 ~ -0.37)*
Physics	OR = 0.84 (-1.02 ~ 1.65)**	OR = 0.65 (-0.34 ~ 1.68)**	OR = 0.87 (-0.3 ~ 1.75)**	OR = 0.54 (-0.228 ~ 1.30)**
Total sciences	OR = -0.45 (-2.35 ~ 1.65)**	OR = -1.06 (-2.28 ~ 0.17)**	OR = 0.52 (-1.35 ~ 2.33)**	OR = -0.16 (-2.02 ~ 1.38)**

- = Negative relationship; ** = Non significant relationship. *Confidence Intervals in parentheses*

Table 6

Firth Logistic Regressions of Grade Boundaries Subject

	1st from a 2:1 (*n* = 635)	2:1 from a 2:2 (*n* = 660)	2:2 from a 3rd (*n* = 301)	3rd from a failing grade (*n* = 84)
Psychology	-.141 (.294)	.549 (.264)*	.432 (.402)	.575 (.549)
Biology	.491 (.178)**	.326 (.190)	.800 (.435)*	-4.01 (.689)
Chemistry	.315 (.238)	.930 (.369)**	-8.16 (.697)	1.027 (1.775)
Mathematics	.215 (.218)	.544 (.255)*	.872 (.690)	-.478 (1.113)
Health and Social Care BTEC	-1.346 (.587)**	-.320 (.301)	.250 (.516)	-1.118 (.549)

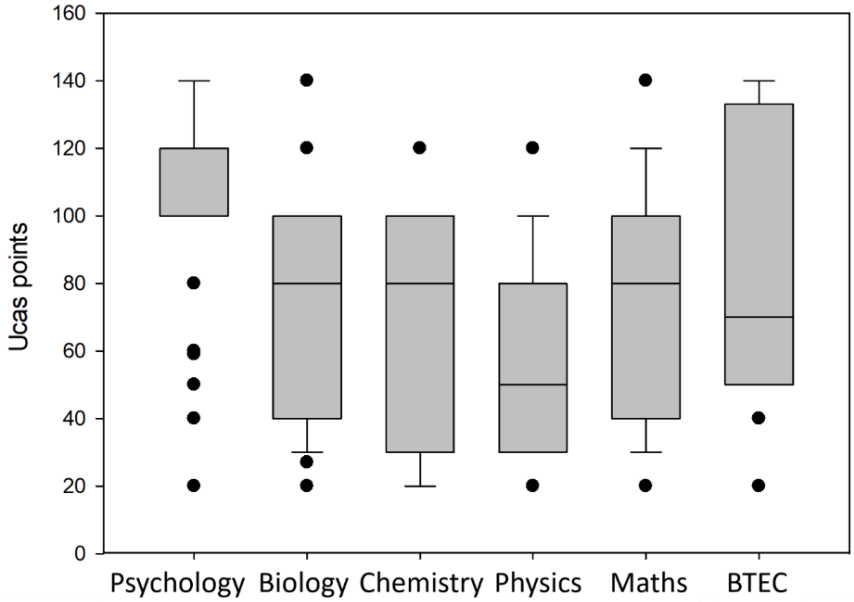
*p < 0.001***, p < 0.01**, p < 0.05*. Standard errors in parentheses*

Having examined the effects of holding a particular qualification, it is important to also consider the level of these qualifications, for example an A* level grade, suggests greater knowledge levels than those gaining a qualification at a grade E.

Figure 3 indicates the distribution of the UCAs points held by the students in the sample, the small number of students holding a Physics qualification is signified by the lower position of the boxplot. Equally, those choosing to study Psychology as an A level tend to be, perhaps unsurprisingly, clustered towards the top end of A-level grade results. Finally, for the purposes of comparison, the UCAS points for BTEC have been divided by three since these qualifications represent UCAS points equivalent to three A levels.

Figure 4

Box Plots Showing the UCAS Point Distribution of the Sample by the 6 Qualifications



Note. Points value range: A-level grade A = 120 points – A-level grade E= 40 points, As level (equivalent to half A- level) = 20 points. BTEC equal to 3X A-levels, therefore points values divided by 3 for comparisons.

Qualification and Module Mark

In order to further explore student's entry qualifications, correlations between A-level entry qualification grades and module scores were assessed. A significant correlation for both Psychology and Biology qualifications within each module and the overall degree grade was found (see Table 7). Mathematics significantly correlated with each module except Social Psychology, which is notable as it is the only module where Mathematics is not used. Significant associations between Chemistry and Psychobiology and overall scores were also found. Regarding the Health and Social Care BTEC only Social Psychology and Research Methods showed a significant association. No significant correlations were found between Physics and any of the scores, again most likely due to low numbers of students holding this qualification and choosing to study Psychology.

Table 7

Correlations between A level Student Grades, Overall Psychology Degree Grade, and Psychology First Year Module Grades

	Overall	Social Psychology	Research Methods	Psychobiology
Psychology	$r(937) = .183^{***}$	$r(938) = .184^{***}$	$r(941) = .145^{***}$	$r(926) = .132^{***}$
Biology	$r(375) = .296^{***}$	$r(251) = .152^{***}$	$r(376) = .249^{***}$	$r(378) = .375^{***}$
Chemistry	$r(128) = .276^{**}$	$r(90) = .942$	$r(129) = .114$	$r(131) = .231^{*}$
Mathematics	$r(165) = .191^{*}$	$r(111) = .879$	$r(166) = .174^{*}$	$r(166) = .187^{*}$
Physics	$r(26) = -.188$	$r(26) = -.169$	$r(17) = -.127$	$r(26) = .104$
Health and Social Care BTEC	$r(76) = .091$	$r(55) = -.478^{***}$	$r(78) = -.350^{***}$	$r(76) = -.170$

$p < 0.001^{***}$, $p < 0.01^{**}$, $p < 0.05^{*}$

Finally, the effects of prior qualifications on overall grade were examined using stepped regression to account for the effects of prior knowledge over the subsequent years of study. It was not possible to do this at a module level as second and third-year models are presented in mixed format (incorporating elements of other modules in terms of research methods, Biology, and cognitive aspects).

The regression model showed that despite influencing first-year grades, entry qualifications had no effect on either second year ($F(680, 1) = .090$, $P = .765$; $\beta = -.011$, $p = .500$) or third year level of studies ($F(680, 1) = 1.425$, $P = .241$; $\beta = -.077$, $p = .970$), suggesting that the effects demonstrated in first year do not persist across the rest of student's degree. Note, for the 2014 cohort the dropout rates were 14 from first to second year, and 4 from second to third. From the 2015 cohort these were 10 and 8, and 12 and 5 for the 2016 cohort respectively.

Discussion

This study aimed to explore whether prior University entry qualifications influenced student overall performance, and if so, which qualifications had a greater association with higher academic performance. The findings suggest there is a definite association between certain prior entry qualifications and various metrics of student success. Specifically, this investigation identified a small but significant effect on each of the six entry qualifications of interest with various relevant modules confirming hypothesis one and two. For example, an association was found between A-level Mathematics and the Research Methods and Statistics module, whilst both A-Level Chemistry and Biology were associated to successes in the Psychobiology module.

Interestingly, the results show when considered alone science-based subjects do produce an advantage for students, however, when taken together (i.e., Chemistry and Biology, vs just Biology) performance effects did not significantly increase, therefore the third hypothesis is rejected. Potentially, this is because the value of such entry qualifications is within developing

the scientific literacy needed to fully identify and engage with the course material, instead of being purely domain specific knowledge. As well as a discrete fact learning pattern, scientific learning also follows a systematic form of knowledge generation, which includes wider skills such a critical analysis and openness to new ideas. Conversely those with little or no knowledge of a scientific topic, are far more likely to consider the learning of science through surface learning behaviours and actions such as memorising formulas to arrive at correct factual answers (Seraphin et al., 2012). An alternative explanation is that much of the base knowledge taught across A-level science topics such as biology and chemistry relate to similar concepts thereby meaning any increase due to holding two A-level science qualifications, compared to the one, maybe was too small to be captured. However, due to variations in course content across various A-level exam boards (i.e., AQA, Edexcel) it was not possible to examine this explanation in further depth.

The examined Psychobiology module covers similar topics to the Biology A-level curricula across several UK exam boards. Students holding the qualification were found to do better than those without. However, this effect was only observed when students obtained higher marks (>60%). Thus, suggesting the advantage of such prior knowledge resulted in students being able to correct any misconceptions and further deepen their understanding of the material when studying the material again as part of the relevant module. Whilst for the students with lower A-level grades, a lack of prerequisite knowledge and conceptual understanding can obstruct deeper learning (Buntting et al., 2006), with misconceptions and misunderstandings persisting, meaning lower performing students are less likely to pass the module and the course at the higher-grade levels (2:1 and above).

Secondly, the presence of qualifications and their impact on grade boundaries was addressed through running ordinal regressions concluding there to be no advantage between those working at the level of achieving a 3rd class vs those failing the course. Potentially, this result may likely be due to other factors affecting student outcomes such as attendance, student ability, focus during lectures, or even due to external factors such as student wellbeing, and mental health (Vaez & Laflamme, 2008). Future studies could consider including some of these additional variables alongside prior knowledge when conducting research. Significantly, there is a slight advantage of prior qualifications on lower performing students possessing a Biology entry qualification. Here it was found that these students are more likely to gain a 2:2 instead of a 3rd class overall grade, suggesting a base grasp of biological concepts is important to those working at the lower end of the distribution.

Conversely for those students receiving a 1st or 2:1, the impact of A level subjects is less clear. Only prior knowledge in Biology was positively and significantly associated with higher performance at the first-class level. Psychology, Chemistry, and Mathematics only showed an effect at the 2:1 level. It can be proposed that students lacking prior knowledge in these subjects would require additional support and are therefore more likely to exhibit study anxiety, at tackling difficult subjects, further hampering their efforts to increase their learning to the same levels of those possessing such prior information. Rayner (2014) reviewed the literature considering prior learning in Biology and noted that along with other concept rich subjects, such as Chemistry and Psychology, Biology gave students a distinct advantage due to the fact they were more likely to achieve higher grades within the Psychobiology module, and to a lesser extent their overall degree mark. This highlights the challenge that educators face in designing curricula at the optimal level, looking to engage students both with and without the relevant qualifications (and/or subject knowledge). This is particularly true for first year

students, and it could be argued, that part of the purpose of first year is to reduce these differences in prior knowledge, ensuring all students start their second year with similar levels of knowledge and understanding. The results here support this idea as the effect of prior learning does not persist beyond a student's first year. Of course, topic and grade level are only two parts of the overall picture and qualification type can also affect how well students perform.

Alongside the standard A-levels this study also considered the effects of holding a BTEC qualification in Health and Social Care. This qualification emphasises several psychological and biological concepts and should in theory offer a good basis for studying Psychology, however findings of this study do not support this assertion. Consistently across the sample, holding a BTEC qualification led to a negative effect on grade boundaries, additionally showing a negative medium-strong association with getting a 1st class degree, suggesting that the prior knowledge gained for the students within this sample did not help performance. It is likely that in general the learning approach utilised for BTEC/vocational qualifications, does not provide a sufficient level of scientific literacy and learning skills needed for higher level study. The emphasis in such courses is focused more on practical skills/information and less on theoretical/academic understanding - for example, the Health and Social Care BTEC suggests discussing intellectual development in terms of ability in different age groups, whereas in A-level health sciences focus is placed on theoretical models and the transitions between life stages. Shields and Masardo (2015) longitudinally examined over 750,000 students and found that students holding a BTEC were more likely to be from areas that typically do not send many students to university, and for those that do go, courses with low entry tariffs are usually the ones which are applied to. Furthermore, even once these factors were considered, students were still less likely to graduate with a 1st or 2:1. Bailey and Bekhradnia (2008) found students taking vocational A-levels tended to be less successful in their studies by having a much higher risk of dropping out and being less likely to get a 1st in their university degree. Shields and Masardo (2015) suggested that these findings may also be weakly related to socioeconomic status, with students from low-income areas being more likely to attend further education colleges where a BTEC qualification may be more prominent. Again, a future study in this area could examine other predictors of success and its effect on qualification type and grade. For example, such studies could examine student socio-economic status which as suggested above have been shown to mediate the relationship between academic performance (Rodríguez-Hernández et al., 2020).

Furthermore, the type of learning required on a degree course is thought to be quite different to a vocational qualification. In order to account for the mismatch between required and held knowledge base, students may adopt ineffective and inappropriate study strategies, promoting further disengagement and attrition leading to increased drop-out rates (Duff, 2004). It must be noted that BTEC qualifications are not designed as a precursor to university study, and most students undertaking this route do not progress onto Higher Education (Economics, 2013). Indeed, the choices made by students when choosing A levels or other entry qualifications could partially explain the findings of this study as an emphasis on scientific subjects sometimes being more prestigious than their arts equivalents (DeGroot, 2016, as cited in Van Rooij et al., 2017). Psychology is sometimes interpreted as a softer science compared to Life Sciences and Engineering disciplines, possibly appealing to those with both arts and sciences background.

The current study has a few limitations. Firstly, it did not consider in depth the role various subject combinations may have played on learning. A future study may warrant examining the data from the broad topic areas of Languages, Humanities, and Sciences, rather than as individual subjects. The study only considered students studying Psychology which is a diverse topic needing knowledge from a range of domain areas. It is possible the results found may be different for other undergraduate programmes, especially for degree programmes that directly link to the prior qualification. Additionally, the study was not able to account for incidental and casual learning that may have occurred alongside formal teaching. It is likely that even if a student did not possess a Psychology qualification, they would still have some awareness or knowledge of the discipline. Therefore, not capturing students' casual prior knowledge is a shortfall. As the current case study only examined one Russell Group University it should be noted that the findings may, at least in part, be the result of the particular course structure and assessment used at the University of Liverpool and therefore it would be useful to consider other institutional factors when designing further studies. The measurement scale used could also have played a part in these findings.

Using UCAS points as a proxy measure for a subject's prior knowledge is also not without its issues. Firstly, it has been noted that the conversion of other qualifications such as the IB and BTEC are not in line with their A-level equivalents. For example, a distinction in a BTEC prior to 2020 was worth 420 points, compared to the 140 UCAS points given for an A-level A*score (Gill, 2018; Seraphin et al., 2012; Shields & Masardo, 2015). Yet most commentators agree that BTEC qualifications do not, in practice at least, amount to three times the equivalent knowledge of an A-level qualification. Such findings suggest that the readjustment of the tariff points system may be beneficial, and indeed changes are now being seen. In 2022 the weighting of BTECs were changed so that a single BTEC course now accounts for 2.5 A-level courses rather than the original score of three which were used in this analysis. Secondly, A-levels are simply the educational step taken immediately prior to University, and it has been suggested that in fact earlier qualifications such as AS levels or even GCSE grades may be a better predictor of academic achievement than A-levels (Partington et al., 2011). It is also possible that the ways in which knowledge is taught and assessed can play a role in how discipline knowledge is acquired and used in the future.

Prior knowledge, although important, is only part of the picture explaining just under 50% of grade variance, with caution being advised when interpreting university entrance scores (McKenzie & Schweitzer, 2001). Other influential factors relating to grade attainment, such as study habits, student engagement levels (Snow, 1989), prior experiences (Baeten et al., 2010; Marton & Säljö, 1976), and student preparedness (Kitchung & Hulme, 2013) should also be considered within future studies. Finally, it may be worth exploring some of the non-learning related factors that could affect student outcomes, such as disability, work/caring responsibilities, or even student wellbeing - all of which could be used as covariates when considering the contribution of prior knowledge to grade variance.

Conclusion

To summarise, this research has shown that prior knowledge of scientific topics (particularly related to Biology), is useful for prospective Psychology undergraduate students in obtaining higher marks within their Psychology degree. Despite this the found effect diminishes after

first year due to current learning overtaking the value of prior knowledge. This small but distinct advantage suggests having a qualification in the sciences generally and Chemistry/Biology in particular should be a requirement for a place on a Psychology degree. Such a requirement would be advantageous for students, allowing educators more freedom to develop their introductory curricula beyond a review of the material they should know at the start of the course.

These findings are based on qualifications alone and only provide a partial insight into the wider picture. It is important when educators consider course design they are mindful of the range of ways prior knowledge can be established, with such knowledge not necessarily so succinctly captured by qualifications. For example, baseline tests could instead be considered by educators, as well as support mechanisms such as extra sessions for lower performing students, more challenging material for higher performing students, and the implementation of peer mentoring to help address any misconceptions that arise. In terms of alternative entry routes these could be adapted to include more scientific content thereby levelling the playing field for students entering through a non-traditional route.

In light of these findings, the University has subsequently changed their policy now requiring students to hold at least one STEM based subject qualification prior to entry onto the course. Initial results suggest that this policy change has benefited students with fewer overall getting third class marks or failing and more working with in the 2:1 grade boundary. It is hoped that future students will now be better prepared for the course's scientific content, subsequently leading to better student performances and final degree marks.

4. Study Two: How does Student Access to a Virtual Learning Environment (VLE) Change During Periods of Disruption?

Abstract

Higher Education often faces disruptions to teaching either due to potential transformations or wider events, such as industrial action by staff or the recent COVID-19 pandemic (Li et al., 2022). Digital learning tools (such as Virtual Learning Environments, VLEs) can be used to support both teaching and learning processes as well as help reduce the impact of disruptive events. For example, the recent global pandemic led institutions to swiftly change their teaching from blended learning to emergency remote teaching (Hodges et al., 2020), where students were directed towards recorded lectures and other materials uploaded to VLEs. As the use of online tools such as VLEs increase, it is important for teachers and institutions to understand how students can cope with such disruptions to traditional pedagogical methods such as face-to-face lectures. This article presents a case study, comparing student VLE behaviour across three consecutive first year cohorts featuring two "typical" university semesters which used a blended learning approach (2016 and 2017), and one semester (2018) which featured industrial action thus deployed a fully asynchronous learning approach. During this action students were expected to use an asynchronous online learning approach, like that experienced by students during the pandemic, but without its potential confounding variables (such as work commitments, illness, or lack of access). Learning analytics from students' activity within the VLE system were collected and analysed. Findings show that high- and middle-performing students tend to increase their use of asynchronous materials to compensate for the lack of teaching, whilst lower-performing students reduce their overall access possibly due to lower levels of self-efficacy and self-regulation. These findings suggest that educators need to consider how VLEs could be designed to support students when learning should be delivered through an asynchronous online learning environment. For example, educators should consider designing VLE spaces that promote flexibility, supporting student self-regulation, whilst also providing clear guidance on structuring learning activities.

Introduction

Since their introduction over 25 years ago VLEs, also known as Learning Management Systems (LMS), have enabled students studying courses to access information asynchronously and/or synchronously. This use of a VLE results in institutions developing large stores of data on student learning behaviour, in the form of VLE traces. Unfortunately, due to the difficulty with collating and analysing such data, this information is rarely used to inform data-driven decisions (Dawson et al., 2010). By 2003 almost 86% of Higher Education institutions were using them to support their courses (Weller et al., 2003), a figure rising considerably over the years to encompass the majority of university taught courses. A VLE system (i.e., Blackboard, Moodle, Canvas) also supports teachers to deliver a blended learning approach allowing them

to upload course materials/assessments, interact with their students, and even gather statistics regarding student participation and engagement (Limniou & Smith, 2010). Allen and Seaman (2010) define blended learning as any course where between 30% to 80% of the instruction takes place online. Courses using a VLE to support blended learning, have been shown to have a small but positive effect on student learning, particularly in STEM-based subjects (Vo et al., 2017). Examining a move to blended learning, Zacharia (2015) examined 29 different online activities and found that while the graded discussion board accounted for 37% of the variance, just 2% of the variance was accounted for by files viewed. A potential explanation for this finding is that in many cases the dominant use of a VLE is that of content delivery (McFadyen & Dawson, 2012). However, it remains unclear how much VLEs influence student learning/grades, as the previous studies have tended to focus on changes within a learning system rather than how students change their behaviour when presented with a change partway through the semester (i.e., move from a blended approach to asynchronous online teaching). One way of further exploring this issue is by examining how students' interactions with VLE platforms may change when they lost the face-to-face teaching elements of a blended approach due to a sudden teaching disruption (i.e., industrial action and lockdown), therefore relying only on online activities.

The recent global pandemic in 2020 "forced" teachers and students to move to emergency remote teaching (Hodges et al., 2020) where many educators utilised a range of teaching styles. For example, distance synchronous teachings through technologies such as Zoom and Microsoft Teams, including supplementary online material with varying levels of success (Bilal et al., 2021), or asynchronous teachings where recorded material was uploaded to a VLE system (Zeng & Wang, 2021; Khobragade et al., 2021). In addition to the move to online learning during a lockdown, students also needed to grapple with many other challenges and confounding factors to their learning such as illness, work responsibility, competence with online learning systems, and even navigating how to do laboratory work online (Bilal et al., 2021). Such asynchronous teaching delivery processes were also implemented over the industrial actions which took place in the middle of the second semester of the 2018 academic year across UK universities (Birgfeld, 2018). This current case study examines data regarding student VLE use in 2018 when staff members at the institution were striking, and the two years prior when teaching was conducted as normal - thereby seeking to isolate the effects of VLE use when all other factors are the same.

A VLE, can be used in a variety of ways from a simple repository of materials up to a fully developed blended learning environment, however either case the VLE will tend to be one of the central focus points of a course, with students accessing materials and learning through the VLE and university course systems rather than on external sites and tools (Dawson, 2010), or social media (Limniou, 2021). As such VLE data traces can be an important way of researching student behaviour within in the digital environment. Such student VLE data can be used in multiple ways but is mostly used to identify at-risk students and to explain variance in learning outcomes.

In a meta-analysis of over 7000 students, Wolff et al., (2013) found that use of a VLE combined with continuous assessment was the best predictor of student dropout, suggesting that monitoring of early use of VLEs could be harnessed to target potentially at-risk students. Additionally, a wide body of previous studies has also examined the predictive value of VLE use for academic performance using various metrics such as hits (clicks on the online learning material/collaborative tools), discussion board posts, and time spent on the VLE platform (e.g.,

Gašević, et al., 2015; Gašević, et al., 2014). One of the most common measures of VLE use in the literature is that of hits on course material. However, these demonstrate an inconsistent picture with studies finding a range of effects from several significant correlations (e.g., Chen & Jang, 2010), through to no significant effect on course material (e.g., Yamaguchi et al., 2019). Another measure of VLE engagement that has been used within research is that of the overall time spent by students accessing the VLE, however at best overall time, shows a weak relationship with student results, regardless of the breadth and diversity of material examined (Biktimirov & Klassen, 2008; Crampton et al., 2012). Other studies have explored the number of hits, with similarly varied pictures. Baugher et al., (2003) suggested consistency of access (as a proxy for distributed practice) was the most important factor for predicting outcomes, while other studies have suggested that access immediately prior to an exam is more important than access at other times throughout the semester (Levy & Ramin, 2012; Park et al., 2016; Rienties & Toetenel, 2016).

The variance in findings regarding the best predictive measure of performance could also fluctuate between course topics. Finnegan et al., (2009) found that there was no single significant predictor shared across all disciplines, and although some variables were identified as significant predictors for individual disciplines same effect was not apparent when the disciplines were combined. Indeed, a similar finding from Gašević, et al., (2016) led them to conclude that to create effective and successful predictive models for individual courses it is essential to include instructional conditions and pedagogical factors (such as whether activities are formative or summative. Therefore, it's important to consider how students interact with different kinds of learning activities.

A review of the literature suggests that some of the individual elements hosted within VLEs could differentiate and contribute to the overall effect on performance. Elements such as stream capture (lecture recordings) and associated PowerPoints have been found to make some difference to grades (O'Bannon et al., 2011; Smeaton & Keogh, 1999; Leadbetter et al., 2013). While the provision of graded discussion boards (Green et al., 2018; Moore & Gilmartin, 2010) and formative assessment (Kavadella et al., 2012; Ćukušić, et al., 2014) both show significant associations with grade. Both discussion boards and formative assessments can be used to demonstrate engagement with the subject being studied. As Nieminen et al*.,* (2004) illustrated, student choices on what, how, or even when to engage in the study was closely connected to students' levels of self-regulation. A student who prefers external regulation is likely to rely more heavily on teachers, peers or study materials, something Khobragade et al., (2021) identified as one of the large barriers to online learning during the pandemic. Equally, weaknesses are also present in student study strategies, such as massed practice and surface learning strategies which can lead to poor educational outcomes (Metcalfe & Kornell, 2005), as can a lack of engagement with course materials (Davis & Graff, 2005). Failing and students passing with lower grades have been shown to use VLEs less than successful students (Sclater et al., 2016; Morris et al., 2005). Indeed, a recent study by Gašević, et al., (2016) found that a 10% increase in access led to a 2% rise in students' average mark, with one of the most reliable indicators of student failure being changes in one's VLE behaviour (Wolff et al., 2013). Unlike face-to-face elements of a course, one's access to a VLE is largely based around asynchronous and independent study habits.

Although asynchronous online elements allow the students to work at their own pace and time, there is often little guidance on how to make the most of these learning opportunities

(McKenzie et al., 2013; Tan et al., 2021). As a result, some students may lack the self-regulation and motivation needed to complete tasks independently, particularly when academic support is absent (Wolters et al., 2005 Martin et al., 2020). This self-regulation in turn is closely linked to academic achievement (Broadbent, 2017). Examining study behaviour Blasiman and collegues (2017) found that students intended to use a variety of study techniques across the course but ended up relying on surface strategies and massed study a few days before the exam. This finding is also echoed by Kornell and Bjork (2007), who concluded that most student behaviour tended to be based on immediate goals such as passing exams, while long-term retention and learning did not feature in their considerations. As a result, students may choose to prioritise immediate concerns over longer-term learning outcomes.

Sansone et al., (2012) argue that learning through a VLE may be particularly sensitive to self-regulatory trade-offs because there is little external monitoring to guide student choices. A compounding factor to these difficulties is that longitudinally students often maintain the same (un)successful behaviours. Persky (2018) measured changes to students learning strategies over time and found that these remained relatively constant throughout the course, suggesting students were not good at adapting their study strategies to changing circumstances. As a result, if students are using successful strategies, then it is likely they will continue to use these successfully, equally those students using less effective learning strategies may struggle to understand how to improve. A further compounding difficulty can be when disruptions and changes occur partway through a course. Such changes can be on an individual level (e.g., illness, poor mental health etc) or on a course-wide level (such as faculty strikes, or the recent global pandemic).

When teaching staff go on strike it is common practice to provide learning materials online so that students are not as disadvantaged as they may otherwise be due to an absence of direct teaching. Typically, these include recorded lectures from previous years and other material designed to allow students to study independently. This provision may in part explain why studies such as that by Jacquemin et al., (2020) found no significant effects of strikes on final grades, while older studies found small, albeit significant effects (Grayson, 1997; Belot & Webbink, 2010; Aremu et al., 2015). However, these studies did not explore student VLE behaviour in depth and did not consider the fact that some students may be more successful than others at switching to using technology as a substitute for face-to-face activities (Bos et al., 2015). Most of the studies discussed above consider student behaviour under normal circumstances and to date, no study appears to have explored student behaviour and how this may, or may not, change during strike action by educators. Based on the literature discussed above and the contrasting findings within it, the current study seeks to examine the following hypotheses:

H_1: Does overall hit consistency accurately predict students' grades?
H_2: Is accessing stream capture and course PowerPoints associated with the final module grade of students?
H_3: Does student behaviour (including hit consistency) change during years with strike action, compared to years with no strike action?
H_4: Does student behaviour change (or not) during strikes compared to their behaviours in periods with no strike action?
H_5: If behaviour does change, does this have any effect on student outcomes?

Methods

Participants

The current study used data traces taken from three large cohorts of first-year undergraduate students and their VLE activity within a biological psychology module presented in their second semester.

Data

The University, based in the Northwest of England, uses Blackboard for its VLE platform. Within the module space, students can see information arranged in a file structure with each week's teaching having a separate folder. Each week's folder contains a recording of the lecture capture, two copies of the lecture PowerPoints (one complete and one with spaces to aid active notetaking), and various other miscellaneous materials, such as supplementary videos and extra information. The module also has a discussion board; however, this is only used by a small subset of students (less than 10%) and is not graded. A brief examination of comments on the discussion board showed these were mostly variations on "will this be on the exam", therefore data from this material source was not analysed further in this study. To encourage distributed practice four low-stakes quizzes (worth 5% each of the overall module mark) are presented in weeks 3, 5, 7, and 9 of a 12-week semester. The content was covered in the first 10 weeks, with week 11 devoted to a revision lecture and the final week being reserved for independent revision.

Data was collected over three consecutive years (2015/16 – 2017/18) by a non-teaching member of staff (a student researcher). The data consisted of the number of hits on each kind of material, with the number of hits per day recorded. This data was then grouped into weekly totals for each of the ten content weeks, the one revision lecture week, a two-week independent revision period, and finally 3 weeks of Easter holidays, as well as pre and post course variables (both of which showed little access, with only a few students accessing the materials either before or after the course teaching dates). In the academic year 2017/18 staff took strike action, which impacted the module under consideration during weeks 5, 6 and 7.

All usage data was downloaded immediately following the completion of the final module exam across each of the three years. Participants were informed about the study prior to the start of the semester via email and verbally within lectures at various points across the module, they were made aware that their study results would not be linked to their academic records, and were also able to withdraw their data should they choose to do so. This study was approved by the University's ethics board (IPHS-2015-2016-411).

Since combined honours students at the University take this module as part of their second year schedule these students were removed from the analysis, as were any who dropped out prior to the final module exam. Any student who failed and subsequently re-took the module had only their first attempt recorded. The resulting dataset consisted of records from 1340 students (roughly 33% from each cohort). Data from overall access to weekly folders was used.

Measures

To examine the individual elements, hits on lecture capture recordings and access to either of the PowerPoint documents were analysed. In order to measure overall hit consistency access to each of the 10 weeks of content, folders were converted to binary values (not accessed =

0, accessed = 1), creating 14 overall hit consistency values (10 teaching weeks, 1 two-week revision period, access pre-course, access post exam and access during three-week Easter break). These were then added together to create a variable of access to each of the content folders at each of the time points.

Analysis

Data was analysed using simple linear regression and a number of MANOVA's to examine the effects of great boundary, and to compare student actions in years affected by striking (2018) with years where normal teaching proceeded (2016 and 2017).

Results

As the aim of this study is to explore students' learning behaviour and patterns regarding the use of VLE in a UK University, the collected data was mainly related to students' grades on online assessments and hits on VLE learning material (i.e., stream capture and PowerPoint presentations). This study also considers the impact of the industrial actions, as part of the students' study disruption.

Data on exam results were significantly different for the 2017/18 cohort, compared to the other two cohorts, with these students scoring significantly more than those in previous years, on both the final module exam (p=.003) as well as in three out of four of the online tests (p> .05). These scores were subsequently transformed into Z scores for the analysis of examining effects on grades.

Overall Hit Consistency (H_1)

A simple linear regression showed that overall hit consistency on weekly folders explained approximately 3.3% of the variance in the four weekly MCT grades (adjusted R^2 =.033, F (14, 1325) = 4.82, p <.001). Specifically, access to course material was positively associated with access in week two (β .068, p = .045), week three (β .078, p = .044), and negatively associated with access in week 10 (β -.088, p = .019). It was also significantly associated with access prior to the start of the course (β .070, p = .011), during the converged revision weeks (β .083, p = .012), and following the exam (β .092, p = .001). Access during the Easter break was not significant (β .001, p = .201), nor was access during week one (β .057, p = .864), week four (β -.42, p = .095), week five (β -.002, p = .276), week six (β .011, p = .117), week seven (β .049, p = .110), week eight (β .005, p = .495), or week 9 (β .038, p = .850).

Further regressions were conducted to examine the effects of each of the four biweekly tests. In the case of test one (which was provided week three, covering material from the start of the course through to week three), the model explained approximately 3.7% of the variance in grades (adjusted R^2 = .037; F (4,1335) = 13.90, p <.001). Specifically, access in week two was significantly associated with grade (β .64, p =. 46), as was week three (β .143, p <.001), however access prior to the start of the course (β .118, p = .189) and in the first week (β -.057, p = .640) were not significant.

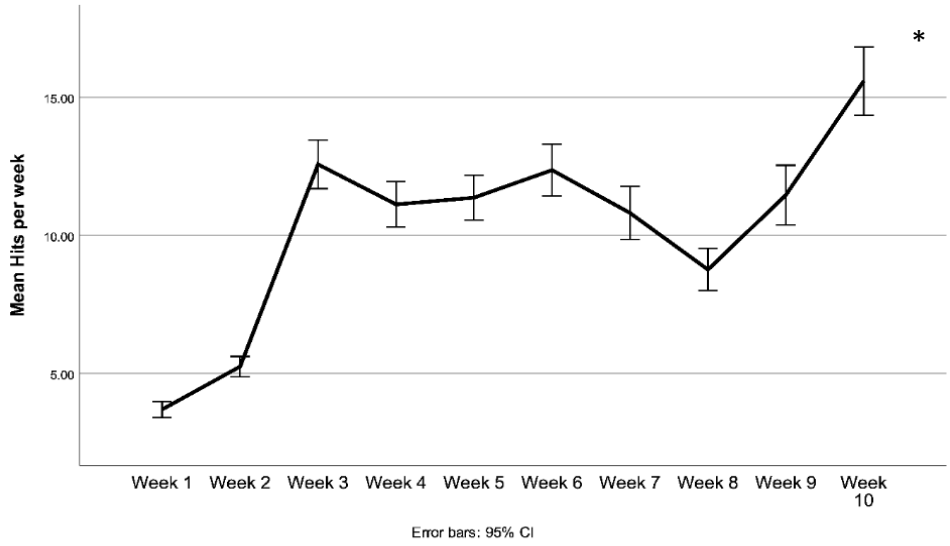
The remaining three tests occurred every fortnight, showing a similar pattern of results. Access to course material was significantly related to the second test (given in week five) explaining 1.3% of the variance (adjusted R^2 = 0.13; F (2, 1337) = 10.10, p <.001). Specifically,

week four was not significantly associated with test results (p = .704) however access in week five was significantly associated (β .114, p =. 001).

Test three (given in week seven) explained 4% of the variance (R^2 =. 040; F (21337) = 28.76, p <.001). Again, week six was not significantly associated with grades (β -.251, p = .996), whilst week seven showed a small but significant grade association (β. 203, p <.001). Finally, test four again showed a similar pattern, the overall model was significant explaining 1.5% of the variance (adjusted R^2 =. 15; F (4, 1335) = 13.90, p <.001), with week eight showing no association (β .118, p = .257) and week nine showing a significant association (β. 148, p <.001).

Figure 5

Line Chart Showing Mean Hit Consistency Across the Module's Teaching Weeks



* Mean Hits during revision period = 62.8

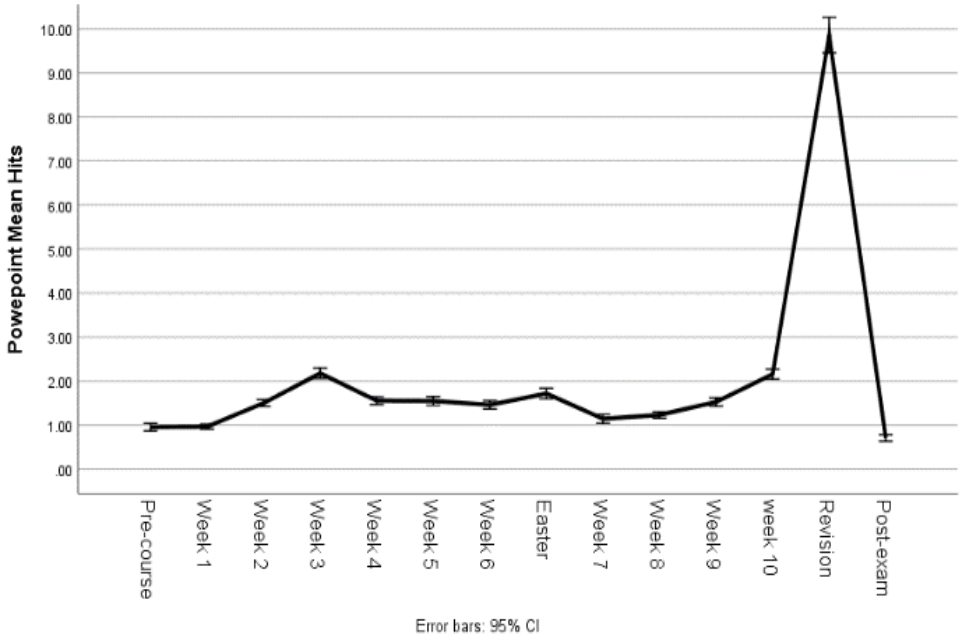
Effects of PowerPoint and Recorded Lecture Stream Capture (H_2)

To explore the effects of individual course elements, data relating to hits on lecture PowerPoints and lecture stream captures were assessed individually and summed as above creating a hit score. Note, since other elements such as supplementary videos and information sheets were not consistent across the module, data relating to these material types were not included in the following analysis. When examining each of the course elements individually, the model shows final grade performs better than overall access predicting 18.1% of the variance in multiple-choice marks (adjusted R^2 = .181; F (27, 1310) = 91, p <.001).

Specifically, access to PowerPoints across the three cohorts was only significant in week six where it showed a slight negative association (β .-62, p <.001), whilst in weeks eight (β .104, p = .001), and nine (β .077, p = .011) a positive association was noted. All other weeks showed non-significant associations: pre-course (β -.021, p = 8.52), week one (β .099, p = .081), week two (β -.042, p = .126), week 3 (β -.010, p =.242), week four (β .001, p = .412), week five (β -.035, p = .195), week seven (β .005, p = .209), the Easter holiday break (β .072, p = .753), week 10 (β .046, p= .535,) revision weeks (β .065, p= .882), and post-exam (β -.150, p= .255).

Figure 6

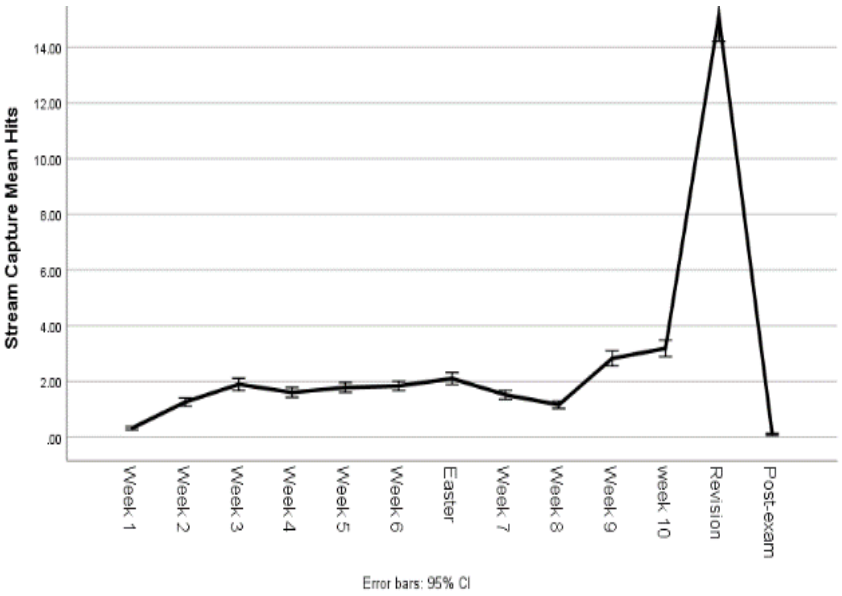
Line Chart Showing Mean Hit Consistency for PowerPoint Access Across the Module



The stream capture of lecture recordings showed significant associations in weeks two (β. 081, p =. 039), week five (β.161, p < .001), week six (β.186, p < .001) and week seven (β. 0.95, p = .001). The remaining weeks were not significantly associated with multiple choice scores at pre-course (β -.012, p = .351), week one (β -.097, p = .484), week three (β-.056, p = .342), week four (β .032, p = .555), during the Easter break (β .027, p = .114), week eight (β.233 , p =060), week nine (β .082, p = .856), week ten (β .123, p = .340), revision weeks (β .003, p = .352), and post-exam (β .010 p = .242).

Figure 7

Line Chart Showing Mean Hit Consistency for Stream Capture Access Across the Module



When examining each of the four tests a similar pattern was seen. The overall access for test one the model explained approximately 1.9% of the variance, R^2= .019, F(8, 1329) = 4 .276, p <.001, specifically PowerPoints in weeks one (β. 086, p = .004), week two (β. 083, p = .013) and week three (β. 092, p = .007) were significantly associated with test one while Stream Capture was not associated with grades in week one (β -.521, p = .539), week two (β -.905, p = .369) or week three (β -.007, p = .369) equally access prior to the start, showed no association with grades for either PowerPoints (β -.002, p = .994) or Stream Captures (β -.226, p = .996).

Test two also showed a significant association between access and skills explaining approximately 2.3% of the variance, R^2= .023, F (4, 33) = 8.707, p <.001, with only access to PowerPoints in week five showing a positive association (β. 091, p = .035). PowerPoint access in week four was not significant (β .024, p = .730) and neither was Stream Capture access in either week four (β -.210, p = .278) or week 5 (β -.521, p = .265). Conversely Stream Capture access was significantly associated with results for test three explaining approximately 7.4% of the variance, R^2= .074, F (4, 1333) = 8.707, p <.001, with both week six (β. 134, p < .001) and week seven (β .268, p < .001) seeing significant associations. Access to PowerPoints was not significant in week six (β .113, p = .488), or week seven (β .098, p = .344). Finally, in the case of test four the model explained 6% of the variance in grades, R^2=. 60, F (4, 13 33) = 8.707, p <.001, with both PowerPoint in week eight (β. 088, p = .003), and week nine (β. 123, p <.001), as well as Stream Capture in weeks eight (β .770, p =. 007), and week nine (β. 167, p <.001).

The Effects of Striking (H_3)

In order to assess whether student behaviour changed during the 2018 strikes, the hit values were converted to ratio values of pre-strike (weeks 1-4), strike (weeks 5-7), post-strike (weeks 8-10), and revision weeks (weeks 11 and 12) to explore the differences between students' access across the weeks. 83 students in this cohort's sample did not access the VLE during teaching weeks 1 to 10 and were removed from the analysis. The same transformation was also applied to individual items (PowerPoint and Stream Capture). In order to examine the effects of VLE access on student's grade boundary, a between subjects MANOVA used grade boundaries (1st, 2:1, 2:2, 3rd, and fail) and strikes (strike/no strike action) as the independent variables and hit values at each of the four time points as the dependent variables.

Results of the MANOVA showed a significant effect of grade boundary on overall hit consistency at all four time points (Pillai's trace = 0.40). Specifically pre-strike F (4, 1330) = 2.48, p = .042 $\eta^2 = .007$, during the strike F (4, 1330) = 8.02 p <.001, $\eta^2 = .024$, after the strike F (4, 1330) = 5.413, p <001 $\eta^2 = .016$, and during that revision weeks F (4, 1330) = 5.413, p <.001 $\eta^2 = .016$. Post hoc tests for overall hits are shown in Table 8.

Table 8

P values of Post Hoc Tests of Grade Boundary on Overall Hits (Bonferrioni)

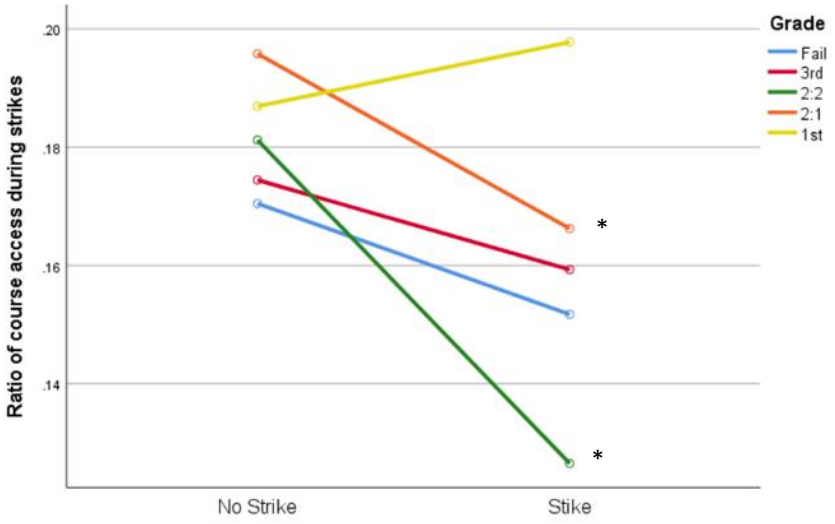
	1st Class	2:1Class	2:2 Class	3Rd Class	Fail
1st Class	-	0.43	<.001	<.001	1.00
2:1Class	0.43	-	.389	.832	1.00
2:2 Class	<.001	.389	-	1.00	.041
3Rd Class	<.001	.832	1.00	-	.097
Fail	1.00	1.00	.041	0.97	-

Results of the MANOVA also showed an effect of strike action on overall hit consistency during each of the four time periods (Pillai's trace = .160), with pre-strike weeks F (1, 1330) = 109.12, p <.001, $\eta^2 = .076$, the strike weeks F (1, 1330) = 14.87, p <.001, $\eta^2 = .011$, post-strike weeks F (1, 1330) = 1127.42, p <.001, $\eta^2 = .076$, and revision weeks F (4, 1330) = 122.47, p <.001, $\eta^2 = .084$.

Additionally, the tests showed there was a significant interaction between grade boundary and year during the strike weeks F (4, 1330) = 3.24, p = .012 $\eta^2 = .010$; however there were no other significant interactions (prestrike F (4, 1330) = 0.39, P = .136, post-strike and revision F (4, 1330) = 1.67, P = .605) see figure 6 below.

Figure 8

Interaction between Strikes and Student Grade Boundary During Strike Weeks (N = 1340)

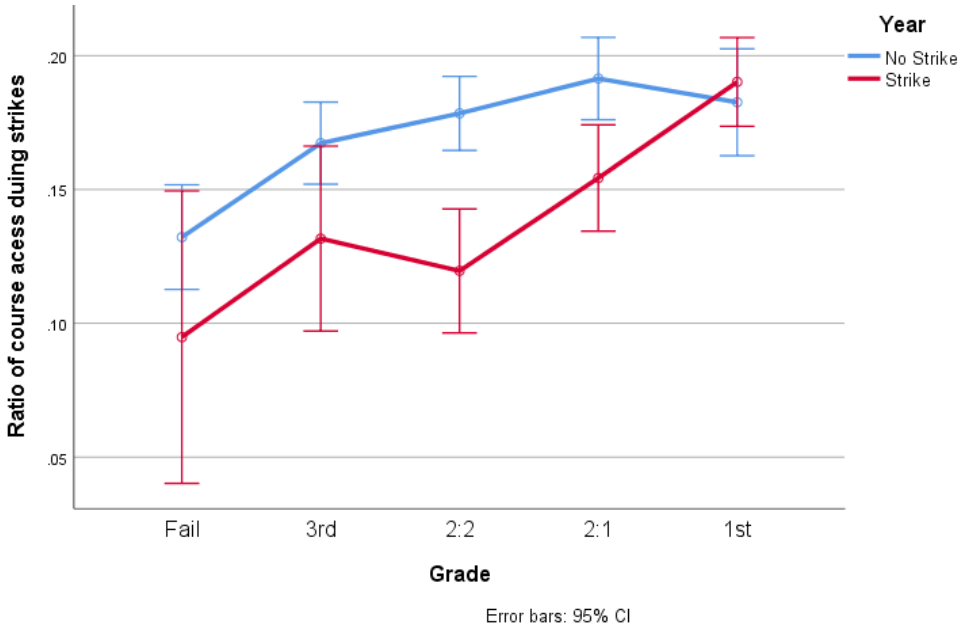


Note. * Significant differences

Specifically, T-tests comparing strike years with no strike years showed first-class students access the VLE considerably higher during strike weeks, however this difference was not significant (p = .551). Conversely, students in other grade boundaries accessed the VLE significantly less during strike weeks showing a significant difference in access levels for those at the 2:2 level (T (337) =4.70, p <.001, d = 0.58), and the 2:1 level (T (312) = 2.91 p = .004, d = 0.32). Both failing (p = .327), and 3rd class students (p = .161) showed no significant difference in access level (see Figures 6 and 7).

Figure 9

Line chart showing overall access to VLE folders split by grade (N = 1340)



The Effects of Striking Across Cohorts (H_4 & H_5)

Access to PowerPoints across the each of the cohorts was also examined using a 4 x 2 between subjects MAONVA. Results showed an overall significant main effect of grade (Pillai's trace = .100 and year Pillai's trace = .039 and an overall interaction Pillai's trace = .023).

Table 9 *MANOVA Between Grade Boundary and Strike Year on Access to PowerPoints*	
Grade Boundary	
Pre-Strike	f (4, 1330) = 2.48, p = .042, η^2 = .007
Strike	f (4, 1330) = 2.48, p = .053, (not significant)
Post-Strike	f (4, 1330) = 5.413, p <001, η^2 = .016
Revision	f (4, 1330) = 50.05, p <.001, η^2 = .180
Year	
Pre-Strike	f (4, 1330) = 3.12, p = .012, η^2 = .010
Strike	f (4, 1330) = 1.88, p <.001, η^2 = .027
Post-Strike	f (4, 1330) = 11.61, p <.001, η^2 = .016
Revision	f (4, 1330) = 19.42, p <.001, η^2 = .028

Additionally, there was a significant interaction between grade boundary and year during the prestrike weeks (F (4, 1330) = 4.04, p = .003, η^2 = .006) and during the revision weeks (F (4, 1330) = 8.33, p =. 003, η^2 = .012). However, both strike (F (4, 1330) = 1.07, p = .111) and post-strike were not significant (F (4, 1330) = 3.17, p = .080).

Results showed similar findings to those for overall access, first-class students did not access significantly more materials prior to the strikes (T (294) = 1.77, p = .406), but did access significantly more materials during the revision weeks (T (294) = 2.28, p = .023, d = 0.19). Students working at a 2:1 level did not access significantly different amounts of materials either pre-strike (T (320) = 2.03, p = .689) or during revision weeks (T (320) = 2.57, p = .406). Equally, students working at the 2:2 level showed no significant difference in access prior to strikes (T (339) = 2.28, p = .351), or during the revision weeks (T (339) = 3.67, p = .351). However, for students at the third-class level, the pattern of access shows no significant difference at pre-strike (T (243) = 3.16, p = .525), but during revision weeks they accessed significantly fewer materials (T (243) = 3.15, p = .002, d =0.34). Equally, for students failing the course, access to materials at pre-strike was lower, and approaching significance = .051, whilst access was significantly lower and during revision weeks (T (44.73) = 4.227, p <.001, d = 0.721).

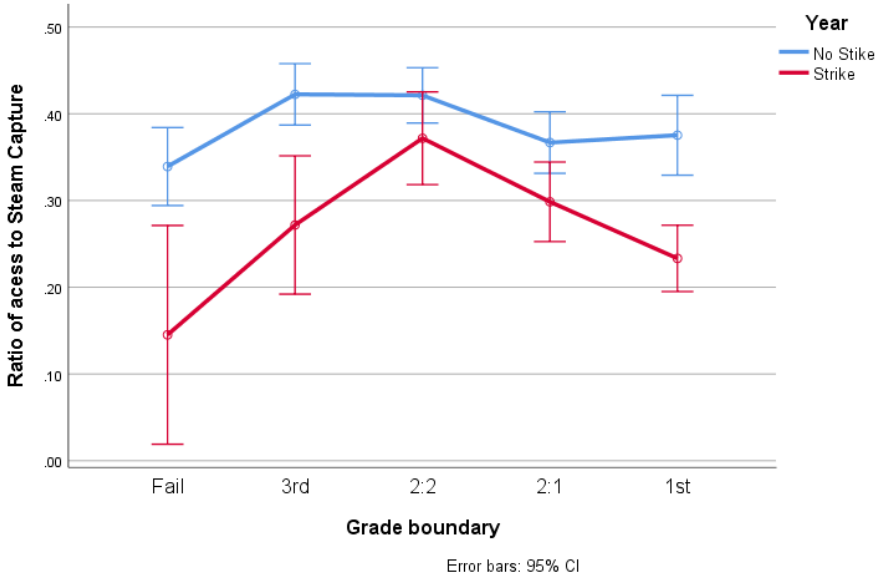
Finally, access to stream captured lecture recordings was explored through a 4 x 2 between subjects MANOVA showing an overall significant main effect of grade (Pillai's trace = .095) and year (Pillai's trace = .346).

Table 10 *MANOVA between Grade Boundary and Strike Year on Stream Capture*	
Grade boundary	
Pre-Strike	F (4, 1330) = 1.23, p =.063
Strike	F (4, 1330) = 10.47, p <.001η^2.031
Post-Strike	F (4, 1330) = 0.73, p =.069
Revision	F (4, 1330) = 6.67, p <.001, η^2= .020
Year	
Pre-Strike	F (4, 1330) = 533.258, p <.001 η^2 =.286
Strike	F (4, 1330) = 1.13, p =.229
Post-Strike	F (4, 1330) = 105.25, p <001 η^2= .073
Revision	F (4, 1330) = 38.68, p <.001 η^{2}= .028

Additionally, there was a significant interaction between grade boundary and year only during the prestrike weeks (F (4, 1330) = 2.66, p = .031, η^2 .008), whilst findings were not significantly different for strike (F (4, 1330) = 0.97, p = .833), post-strike (F (4, 1330) = 1.33, p = .898), and revision weeks (F (4, 1330) = 0.78, p = 0.68) (see Figure 6).

Figure 10

Access to Stream Capture Split by Grade Boundary



Discussion

The current case study sought to examine student behaviour in accessing course materials on a VLE platform both under normal and disruptive teaching conditions. The results showed students of differing ability engaged in differing patterns of access, but all students tended to mass their access at the end of the course, just prior to exams. Furthermore, low stakes quizzes whilst slightly increasing access during the weeks they were due, they did not consistently and significantly affect use.

Overall hit consistency showed that access towards the start of the course was positively associated with grades, whilst access during the final teaching week was negatively associated to grades. However, in general, regular access across the course did not significantly predict findings. Equally, although the variance explained by PowerPoints and Stream Capture recordings specifically explained more of the variance, hit consistency did not show a relationship between final module grades. Additionally, in the case of each of the four tests, the picture is varied, with access during non-test weeks being slightly lower and overall is not connected with access to course materials. However, when these are examined in terms of individual PowerPoints and Stream Captures these show an increasing association with test grades suggesting that as the material becomes more complex students are accessing the material more frequently. Indeed, the results of the MANOVA show an increase (albeit a gradual one) in access to material across the course with slightly more access taking place in test weeks than non-test weeks. This coupled with the large spike in course access during revision weeks suggests a tendency for students to engage in the massed practice - a finding similar to that found by Levy and Petrulis (2012).

There are two possible explanations for this finding, firstly the variation in access to material suggests that only the most engaged students were regularly (i.e., weekly) accessing the course material. These were also the students who were more likely to access the material at other times (such as during breaks, before and after the course). Because there were four tests

presented across the course designed to encourage distributed practice, students were overall accessing the course materials on the VLE approximately every two weeks, a factor which may have moderated the findings. Indeed, it is likely that a course without such a test would show a still stronger effect of massed practice at the end of the course. The significant finding for access during the revision weeks matches other similar studies such as that conducted by You et al., (2016) showing that most students tend to focus their attention/time in the period immediately prior to an assessment. The significant correlation between hits during the revision weeks and grade suggests that the course design only had limited effect in encouraging regular engagement. Taken together these findings support the previous literature finding that although hit consistency only weakly predicts overall grades, the variance predicted and its effect are minimal. Further these findings are likely being driven by students' levels of self-regulation meaning those with higher levels of self-regulatory behaviour are also consistently more likely to engage with the course on a regular basis. High level of self-regulation could therefore explain more frequent use of a VLE system, and as Carter et al., (2020) notes this is a vital component to consider when designing online learning.

In examining the effects of strikes, students (except first class ones) accessed the VLE less throughout the 2018 module. The patterns of usage behaviour highlighted above suggest that students may have accessed the VLE less in the weeks prior to the first biweekly test. At this point students would have been aware of the forthcoming strike and may have made a conscious decision to focus on other priorities/modules within their course such as upcoming coursework, perhaps planning to revisit the materials once the strikes had concluded. The finding that access to PowerPoint during the revision week increased for first-class students, remained the same for those at the middle grades (2:1 and 2:2) while dropping further for failing and third-class students suggest that those working at different grade levels will respond differently to any challenges of access. Indeed, a recent study looking at Veterinary Science and Psychology student's behaviour during the recent pandemic (Limniou et al., 2021) showed a similar relationship between student use of digital tools during lockdown and their self-regulation which in turn demonstrated an effect on grade boundaries. In considering the use of recorded lectures through Stream Capture, an unexpected finding was that this technology was used more by students in non-strike years. Although during the strike weeks, lecture recordings from previous years were uploaded, it appears that many students chose not to make use of these. It's possible that this finding could suggest that students valued live lectures over recorded ones. However, as this finding is contrary to similar studies showing that on the whole students prefer recorded lectures (especially those with disabilities and English as a second language e.g., Porter et al., 2021), it would be worth exploring this result in more detail in a future study. Overall, the findings suggest that students working at the first-class level changed their approach to the material, increasing their access, specifically accessing PowerPoints and ancillary material (such as web links or articles) more. At the same time, these students made less use of Stream Captures, than those in the middle-grade boundaries (2:1 and 2:2) who did not appear to change their access behaviour as a result of the strikes. Finally, those at the lower end of grades (3rd class and failing) made less use of the VLE consistently throughout the course only increasing their access slightly during revision weeks. This result could potentially be explained by decreasing motivation, further exacerbated by poor self-regulation during strike action.

The overall picture presented by these findings suggests that students can be clustered according to their grade boundary and that each of these groups will respond differently to

changes in the teaching environment. Although not directly measured in this study it would also appear that students who have higher levels of self-regulation find it easier to adapt to changes in teaching (such as strikes or the recent move to emergency remote teaching) by changing their study habits to most effectively make use of the material provided (Believe et al., 2021). For example, by encouraging increased access and/or accessing different types of course materials. Additionally, those who struggle with self-regulation, are likely to find independent study more difficult and when faced with no immediate need to access the material, may procrastinate, and put off access until shortly before the exam. Indeed, although the tests were worth 5% of overall grade several students chose not to take these tests at all, in particular, several students chose not to take test 3 across all of the three cohorts studied, this could have been as they had other coursework deadlines at this time. Having said this, access to materials was not significantly different for students between strike and non-strike years suggesting that this finding may relate more to students' self-regulation levels experiencing a mid-term drop-off in engagement which then translates into reduced access to the VLE more generally.

This study has a few limitations, the design of the VLE meant that students were able to download materials in advance (with the exception of the recorded lectures) and could have been shared these by other means, thus resulting in analytics showing the student only ever accessing the VLE once. Other students will have accessed the material every time they wanted to consult it. Additionally, the system only recorded clicking on each of the materials, meaning recording engagement with the course materials was unable to be gathered. This weakness may go some way toward explaining the low effect sizes found by this study. Since VLEs have become more sophisticated the quality of available learning analytics has improved with many VLEs (e.g., canvas) providing much richer data regarding student interaction with course materials. Secondly, the current study only examined first-year students studying a single online module within a Psychology course. Specifically, our research shows this biological module to be more difficult for students without an A-level in biology and/or chemistry (Hands & Limniou, pending publication 2022). As such, future studies should therefore consider comparing findings across disciplines and/or differing year groups, since it is likely that both domain, study stage, and prior qualifications held by the students affected these results. Indeed, while first-year grades varied due to the strike these did not vary to the same extent as other modules for the same students in subsequent years of their degree.

The current study offers a brief overview of how basic learning analytics can highlight how students change their behaviour both according to their academic ability (i.e., grade boundary) and external changes such as a faculty strike, individual circumstances, or even a global pandemic. These findings can help inform effective learning design, highlighting the importance of encouraging regular distributed practice and supporting weaker students to increase their levels of self-regulation. Perhaps the most important implication of this study is related the use of learning materials that students can access and work on independently in the event of disruption to face-to-face teaching, whatever the reason behind this may be. This study demonstrates that while at least some of the disruption caused by these events can be mediated, it is not enough to simply provide materials that give the same information as a face-to-face lecture, but instead need to be redesigned for an online asynchronous audience. Current best practice suggests that flipped classroom models, short (10-20 minute) videos of material, alongside regular low stakes assessment works well in both online and face-to-face

scenarios (Murillo-Zamorano et al., 2019; Al-Samarraie et al., 2020); thereby offering students the best possible outcomes regardless of the means of accessing learning.

5. Study Three: A Longitudinal Examination of Student Approaches to Learning and Metacognition

Abstract

Student Approaches to Learning (SAL) mainly consists of two contradictory approaches (surface and deep learning) to learning that have been extensively studied in educational research. Metacognition, which refers to the process of thinking about one's own thinking, has been shown to play a crucial role in helping students shift from a surface to a deep approach to learning. By becoming more aware of their own learning strategies and thought processes, students can improve their overall academic performance and develop a deeper understanding of the subjects they are studying. The current study collected data using two questionnaires (RSPQ-2F& MAI) from 1329 data points (944 at one time point and 385 at 2-time points). The data were gathered from the whole cohort at the start of semester one and the study was then repeated in semester two of their second and third years of study. Both metacognition and learning approaches showed medium correlations and an effect of the year of study. A crossed lagged model shows no effect of deep learning on metacognitive knowledge or regulation although this does increase significantly over time. Overall, the study's findings suggest there is a complex yet clear relationship between student learning approaches and their final grade outcomes. Students will lean towards more surface learning as their (perceived) workload increases, and assessments become more challenging. Taken together these findings suggest that teachers and policy makers should seek to find ways of increasing deep learning methods, possibly using metacognitive skills training.

Introduction

Higher education seeks to promote students in developing effective approaches to their learning, producing versatile graduates who can apply the knowledge gained in their studies to their careers (Lees, 2002). It is often assumed by teachers that students will develop increasingly "sophisticated" learning strategies (such as self-regulation, metacognition, and deeper learning strategies) as they pass through university (Hofer, 2001). By the end of their studies, students should exhibit self-regulated learning behaviours acting as active agents across their own metacognitive, behavioural, and motivational learning processes (Zimmerman & Schunk, 2012). To track this development one approach could be to examine whether students' approaches to learning and their metacognition change over time.

Metacognition is defined as the intelligent monitoring and knowledge of one's own cognitive strategies (Flavell, 1979) and is a form of executive control that involves monitoring and self-regulation strategies (Schneider & Locke, 2002). Broadly speaking the definition of metacognition is the process of reflecting on and directing one's own thinking (Seraphin et al., 2012), in turn helping a learner understand and control their own cognitive processes (Jaewoo & Woonsun, 2014). By longitudinally examining student metacognition alongside

their deep and surface learning approaches teachers could have a clearer picture 71tudentt learning development patterns. Gaining this information, teachers may amend and/or improve their teaching process in order to enhance the student learning experience and improve student academic outcomes/performance.

Student Approaches to Learning

SAL appear to be a universal experience within education and have been studied worldwide in a variety of settings and subject areas (e.g., Chan, 2010; Fyrenius et al., 2007; Munshi et al., 2012; Mogre & Amalba, 2014; DeRaadt et al., 2005). Deep learning approaches encourage greater learning breadth and depth (Felder & Brent, 2005), resulting in the transfer of knowledge to novel situations. A deep approach is generally associated with active learning (Gomes & Golino 2014), whereas a surface approach is generally associated with passive learning processes. Surface approaches are often rooted in a desire to pass assessments whilst minimising effort, resulting in focusing on memorisation of material, which is quickly forgotten (Ramsden, 2003). Surface techniques include reviewing material presented by the teacher (Waters & Watters, 2007) and passively memorising discrete facts (Stanger & Hall, 2012). These techniques are often seen in those with low academic self-confidence (Sander & Sanders, 2003) as such students tend to focus on what they believe is "productive" learning, in fact, they are merely memorising the details. Surface learning tends to arise from motives extrinsic to the learning task itself whilst deep learning is conversely linked to intrinsic task motivation (Phan, 2011). SAL has also been linked with other traits/characteristics such as openness (Chamorro-Premuzic & Furnham, 2009), positive emotion (Trigwell et al., 2012), and self-regulation (Heikkilä & Lonka, 2006). These characteristics that have all been found to be highly correlated with academic success (e.g., Richardson and Bond 2012). Previous researchers have also examined students' learning approaches across various disciplines it has been found that social sciences, humanities, and the arts cultivate deeper student approaches to learning (Tomanek et al., 2002; Lizzio & Wilson, 2004), while shallower (i.e., surface) learning approaches have been documented in the fields of medicine (Rajaratnam et al., 2013) and the sciences (Lopez et al., 2013; Montplaisir, 2004; Kember et al., 2008; Watkins & Hattie, 1985).

Due to the variety of factors potentially affecting SAL, some researchers have argued for the need of considering a third approach to learning - strategic learning (Biggs et al., 2001). Whether strategic learning is in fact a separate approach or merely a subcategory of the deep learning approach remains highly debated (Richardson 2000; Zeegers 2004). This debate arises as within the literature the use of a learning approach is frequently presented as being mutually exclusive within the dichotomous scale of recognised approaches (i.e., deep vs surface level). However, when the most successful students are presented with a task, they often apply a combination of deep and surface learning techniques to utilize the advantages of both approaches (Baeten et al., 2010). Thus, when considering learning approaches as dichotomous in nature, the nuance within SAL is overlooked (Loyens et al., 2013). Competency may also play a role in how effectively students use either approach. For example, a student following a deep approach, who is not particularly competent would likely not perform as well as one exhibiting a highly organised and well-planned surface approach (Tickle, 2001). A further complicating factor is that students will tend to have an overall predisposition for their favoured learning approach thus limiting their ability to switch

between tasks requiring the application of different approaches. As such, final exam results are often lower than the student's expected grade, particularly for those who exhibit poor metacognitive awareness (Kember & Gow, 1989).

Furthermore, external factors such as the stage of learning, course topic, prior knowledge (Daly & Pinot de Moira, 2010), perceptions of teaching (Pimparyon et al., 2000), and the time point in the academic cycle could affect the use of both deep and surface approaches by students (Entwistle et al., 2000). When students first begin their studies, Elliot et al., (1999) suggested that a surface learning approach was essential for students to become accustomed to the basics and likely be the approach utilized within their initial assessments. Indeed, to develop a deeper understanding of the learning material, students first need to learn basic terms and definitions using surface approaches, such as memorising, before they can synthesise and connect this information on a deeper level (Jehng et al., 1993). At the start of their studies, the fragmented nature of student knowledge means students are more likely to use surface strategies to make sense of the material (Alexander, 2003). Individuals who possess a stronger foundation of basic knowledge are more likely to achieve a deeper understanding and integration of subject material, which supports a more profound approach to learning. (Biggs & Tang, 2011)

Another factor that may lead students to adopt a learning approach developing a potential attitude towards learning is the study time during a demanding period. For example, Fincher et al. (2006) showed that time pressure, both actual and perceived, as being one of the primary drivers leading to the increased usage of surface approach learning strategies, particularly in short, high workload periods, as such examinations (Rønning, 2009). Furthermore, this effect is even more pronounced if students consider their perceived workload inappropriate or excessive (Drew, 2001; Lawless & Richardson, 2002). The regression from deep to surface level approaches because of time pressures has also been evidenced by Baeten et al., (2013). The researchers found students who initially exhibited high levels of deep learning approaches at the start of their studies, shifted to more surface level approaches as a likely effect of time pressure overwhelming their initial motivations to study more deeply (Baeten et al., 2013). Particularly since students attend more than one module at a time, the surface learning approach of memorisation is often favoured over deep learning approaches to help manage both one's workload and time (Yonker, 2011).

As well as being affected by time pressure, a SAL can also vary based on the task activity, such as working on essay or studying for an exam (Dahl et al., 2023; Hadwin et al., 2001). Due to students preferring coherence between their chosen approach and the demands of the learning environment, the approach taken is often context dependent (Entwistle & Peterson, 2004; Vermunt, 2005). Indeed, learning approaches during study periods are often aimed at fulfilling short-term goals such as passing an examination over the longer-term aim of learning and study retention (Kornell & Bjork, 2007). Motivated by these short-term goals, Struyven, Dochy, and Janssens (2003) have suggested that students would employ a learning strategy which they feel would best lead to their desired outcome. This notion was also supported by Gijbels and Dochy (2006) who found that students tended to change their approaches and implement more surface strategies after experiences with formative assessments that did not require deep learning strategies.

Therefore, students would change study processes according to their perception of assessment requirements, following a strategic approach (Marton & Säljö, 1976). This could explain why students tend to score higher than expected when using surface approaches on assignments that they *perceive* require this approach (Ngidi, 2013). This in turn may lead students to interpret the learning environment as one where a surface approach is the best learning tactic (Liem et al., 2008). Equally, students who take a deep approach to their studies would prefer assessments that promote subject cognitive understanding. Including different kinds of questions, assessments might promote either a deep or a surface approach to the material a student has studied. Examinations, that take the form of a Multiple-Choice Test (MCT), tend to set questions at a lower level of understanding and therefore do not require students to synthesise or apply knowledge to a deep level. When students academically succeed in using a purely surface approach (Gulikers et al., 2006; Scouller, 1998), they may become accustomed to or habitually rely on using this approach throughout their studies. Critically, students may then fail to recognise when other approaches would be of more use and adapt their learning patterns accordingly. It is therefore important for both students and teachers to have an awareness of the variety of approaches available and for teachers specifically to accommodate and encourage all forms of uses.

When considering the effects of learning approaches on academic achievements, the literature is somewhat mixed. Richardson, Abraham, and Bond (2012) found in their systematic review and meta-analysis, a deep approach to be positively correlated with Grade Point Average (GPA). Similarly, a range of studies have found that students focusing on a deep approach tend to be more successful academically (Duff, 2004; Zeegers 1999; Liu et al., 2015). Equally, Snelgrove and Slater (2003) found tertiary students who follow a predominantly surface approach are more likely to receive lower grades and are therefore less likely to progress to postgraduate study. Conversely, other research studies have found that surface and strategic-achieving approaches are more predictive of a higher GPA, especially in students with higher academic capabilities. This finding is possibly due to students' ability to recognise and adapt their approach to the type of assessment at hand (Ramburuth & Mladenovic, 2004; Hall et al., 1995). Furthermore, some studies have found no relationship between the learning approach taken and one's grade (Al-Alwan, 2013; Cassidy & Eachus, 2000; Baeten et al., 2008; Gijbels et al., 2005). In his meta-analysis, Watkins (2001) examined data from 27,000 students and found weak correlations between academic achievement and SAL. Lastly, some studies have found support for both approaches. Salamonson et al., (2013), suggest that *both* deep and surface approaches are independent and significant predictors of academic performance. However, all the relationships reported were somewhat weak reiterating our point - the literature remains mixed. One potential explanation for the contradictory findings discussed above could be that students cluster in two different groups according to their approach. There is also increasing evidence that within individual course lessons (and even individual tasks), students tend to cluster into groups based on their approaches to learning (Vanthournout et al., 2009; Leung et al., 2006; Nijhuis et al., 2008).

Fowler (2005) found that deep learners tended to keep their deep approach, whereas surface learners tended to adjust their approach when prompted by the learning environment. These findings suggest that learning trajectories could vary longitudinally. May et al., (2012) also found higher performing students tend to focus on deep learning, whilst those in the bottom quartile show significantly higher surface approaches. Skogsberg and Clump (2003) found no

difference between upper and lower-division students suggesting that increasing topic proficiency was not necessarily accompanied by a change in the learning approach. It is possible this finding could be driven/related to changes in student metacognition (Case & Gunstone, 2002). Studies have shown that students with good metacognition skills are more likely to review and relearn imperfectly mastered material due to their ability to better distinguish between what they do and do not know (Everson & Tobias, 1998).

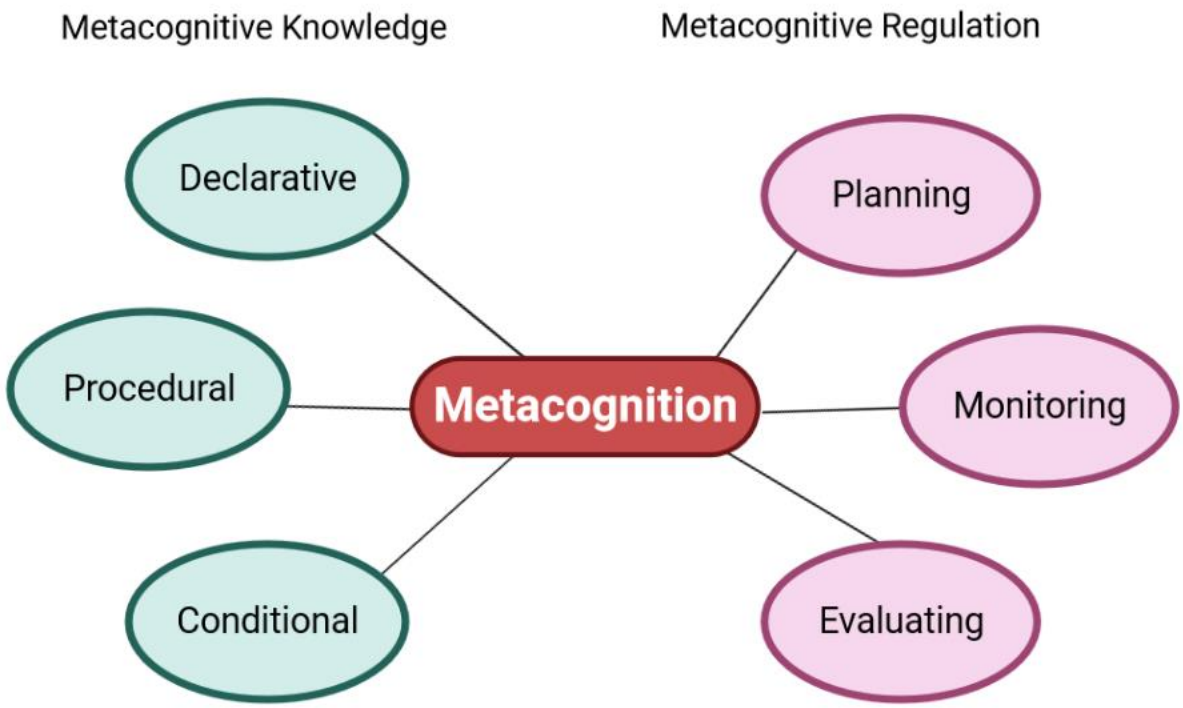
These individuals also tend to adopt a deeper approach to learning, characterized by a focus on understanding and meaning-making rather than surface-level memorization. On the other hand, individuals with weaker metacognitive skills may struggle to engage in strategic and reflective learning activities, and may instead rely on more passive learning approaches, such as rote memorization or repetition. These individuals may also adopt a more superficial approach to learning, focusing on meeting requirements or completing tasks rather than seeking a deeper understanding of the material (Case & Gunstone, 2002). The study strategies associated with a deep approach such as reading widely and making connections with prior knowledge require a student to monitor their own learning process. Thus, being able to reflect on learning and change such approaches based on previous experiences is only possible with a well-developed metacognitive regulation ability (Ridley et al., 1992). Metacognition and approaches to learning are strongly related to learning activities there is a strong relationship between metacognition, approaches to learning, and learning activities. This means that how individuals approach their learning is influenced by their metacognitive abilities, which in turn impact the types of learning activities they engage in. For instance, individuals with strong metacognitive skills tend to engage in more strategic and reflective learning activities, such as setting goals, monitoring their progress, and evaluating their understanding.

Metacognition

Expanding the discussion around metacognition regulation, this is only one of two theoretical areas with metacognitive knowledge to be the other one, (see Figure 9). Metacognitive knowledge refers to students' knowledge, beliefs, ideas, and theories (Veenman et al., 2006) about people as "cognitive creatures" (Zohar, 2015, p.123). In other words, what they know about declarative, procedural, and conditional knowledge (Baker, 1991) which in turn determines task performance (Filho & Yuzawa, 2001). On the other hand, metacognitive regulation, sometimes referred to as metacognitive skill (Flavell & Miller, 2002), is a more active process that applies metacognitive knowledge to the task at hand (Pintrich et al., 2000; Poh et al., 2016). Metacognitive knowledge includes a level of awareness about the cognitive processes one uses to learn and remember (Ormrod & Davies, 2004). Both metacognitive knowledge and regulation improve as expertise in the subject domain increases (Pressley & Ghatala, 1990), although this can vary depending on the domain level studied (e.g., global vs course level; Winsler & Huie, 2008). The two metacognitive constructs - knowledge and regulation - are strongly correlated without a compensatory relationship occurring. In other words, high levels in one construct do not compensate for a lack in the other (Sperling et al., 2004).

Figure 11

Metacognition breakdown. Modified from Schraw and Moshman (1995)



Metacognition is influenced by goals, motivations, and perceptions of ability (Mahdavi, 2014) which all feed into the learning strategies students select to use (Luwel et al., 2003). These strategies may play a mediating role between a student's internal knowledge construction and the external coursework demands placed upon them (Akyol & Garrison, 2011). Students using deep approaches show evidence of techniques such as reflection, questioning, error detection, critiquing, and considering alternatives to their ideas. Research shows that metacognition develops partly independently of intelligence albeit to a limited extent (Berger & Reid, 1989). Therefore, it could be argued that metacognition is mediating the development of intelligence and the learning strategy adoption from students.

Biggs (1985) pointed out that inappropriate surface strategies could not be the result of a lack of metacognition but could be used out of habit or despair, potentially due to workload management as discussed above. Yeşilyurt (2013) found that metacognitive awareness accompanied by an achievement focused motivation was associated with deep learning approaches in students, while Magno (2009) found that using deep approaches accompanied by metacognitive outcomes increased student self-efficacy (confidence in ability). Thus, the conditional knowledge from this approach triggers the use of metacognitive control to select the most effective study techniques (Hadwin et al., 2001). For example, Patterson, Tormey and Richie (2014) found higher levels of student metacognition were related to a strategic approach increasing. Indeed, a shift in learning approach can often be triggered by a combination of (both supportive or detrimental) course environments and their effect on a student's metacognitive development (Case & Gunstone, 2002).

Metacognition is not always explicit as some students struggle to explain their thinking processes (Schraw et al., 2006) coupled with the fact that it can also be difficult to teach these skills and introspection directly to students (Vos, 2001). The effort however appears to be worth it (Schuster et al., 2020). Regardless of the subject, relevant literature suggests that explicit metacognition training can improve performance among students (Thiede et al., 2003). In their meta-analysis, Donker et al., (2014) examined 95 different learning inventions and found metacognitive knowledge instruction had the greatest effect. Rezvan, Ahmadi, and Abedi (2006) found that metacognitive training was especially helpful for students in danger of losing their place at university. Latawiec (2010) suggested that metacognitive strategies could improve reading comprehension in students studying a second language. Further, Choy & Cheah (2009) suggested that the use of metacognitive scaffolding (prompts, keywords, etc.) could help students develop better metacognitive skills, especially novice learners (Lehmann et al., 2014). When students approach learning with higher metacognitive awareness, they tend to have better self-regulation skills which may improve their academic performance (Sungur, 2007).

Metacognition has also been linked to other effective study habits such as critical thinking (Magno 2010; Lai 2011; Ko & Ho 2010), self-efficacy (Coutinho, & Neuman, 2008), self-regulated learning (Duncan & McKeachie, 2005; Marzouk et al., 2016) and spaced learning, that is repeating information and regularly spaced intervals to aid its longer-term retention (Son, 2004). Metacognition has also been linked to intrinsic factors such as a high internal locus of control (Arslan & Akin, 2014; Hrbáčková et al., 2012), self-confidence (Kleitman & Stankov, 2007), and motivation (Tobias & Everson, 2009). In Hattie's (2009) meta-analysis, teaching approaches that emphasised student metacognitive skills and self-regulated learning were among the most effective approaches found, producing a mean effect size of 0.67 similar strong effect sizes have also been found by De Boer et al., (2018), and Guo (2022).

Effects of Metacognition on SAL and Metacognition Measure Tool

Having the awareness and knowledge, along with the ability to monitor, regulate, and apply appropriate learning approaches to any given task is where metacognitive functioning intersects with SAL (Baeten et al., 2010). Through engaging in metacognitive thinking, students can assess and monitor how their current learning approach works and whether any adjustments are needed to learn and retain at a higher efficacy (Flavell, 1976). Within the literature Stanton et al., (2015) found when examining an introductory Biology class, nearly all students moderated their learning approaches in response to task demands but their capability to monitor, evaluate, or plan their own learning strategies (i.e., attributes of poor metacognitive regulation) varied considerably. Similarly, students lacking in metacognitive knowledge can find it hard to judge accurately their (lack of) understanding (Borkowski et al., 2000). This inability hinders learning, causing students to overestimate their performance, under-prepare for examinations, poorly manage their academic performance, and increase the likelihood of dropouts (Sperling et al., 2004; Ryan & Glenn, 2004). Perceived and actual levels of knowledge do not always align (Ziegler & Montplaisir, 2014). Additionally, students might have different criterion tasks in mind when making such metacognitive judgements (Pieschl, 2009). It is critical to note that metacognition is highly contextualised and depends on multiple factors including the type of task students undertake, previous knowledge, and levels of task focus (Zohar, 2013). To engage in high metacognitive functioning students are

required to have what Pintrich and DeGroot (1990, p.39) defined as “the will and the skill”. Therefore, it is important to recognize that metacognitive judgments may not always align with actual levels of knowledge and may depend on various contextual factors, as well as the individual's will and skill to engage in high metacognitive functioning. In this regard, developing self-knowledge is also critical for effective self-regulation and the implementation and monitoring of learning strategies. Local and global monitoring techniques can be used to measure ongoing and cumulative regulation, respectively, with students being more accurate in making global predictions about their metacognition.

Alongside this point, self-knowledge (awareness of feelings, attributes, motivations, and abilities in learning) is also assisting students to understand what learning approaches work best for them to implement and monitor the effectiveness of learning strategies (i.e., self-regulate; Hayat et al., 2020). For example, students may follow local and global monitoring techniques regarding self-regulation where students need to be aware of how they conceptualize (meta)cognition, motivation, and emotion to be strategic and successful (Panadero, 2017). Local monitoring plays a role in measuring ongoing regulation, whereas global monitoring is rather a measure of cumulative regulation (Young & Fry, 2008) with students tending to be more accurate when making global predictions about their metacognition (Nietfeld et al., 2005).

In an effort to assess student metacognition - and its two theoretical components of knowledge and regulation – educational researchers have used the Metacognitive Awareness Index (MAI; Schraw & Dennison, 1994). The index comprises two subscales, knowledge of cognition and regulation of cognition, containing 17 and 35 item questions respectively. The MAI has been shown to have high validity. Schraw and Dennison (1994) found students tended to hold similar metacognitive knowledge, but varied greatly in their levels of metacognitive regulation, with only knowledge of cognition scores significantly predicting test results. Young and Fry (2008) also found significant associations between MAI outcomes and grades among higher education students. Graduate students tended to show better regulation of cognition than undergraduates, however, within each group levels of metacognitive knowledge remained stable. Supporting this differentiation research shows experienced students tend to differ in their use of regulatory skills, such as accuracy monitoring (Schraw, 1994).

As with SALs, researchers have suggested that students could be clustered for analysis according to their metacognitive skills (Stanton et al., 2015). This clustering of different types of students potentially explains the variation in the reported effectiveness and benefits of student interventions such as study skills classes (Vermetten et al., 2002), as well as academic growth/development (Shivpuri et al., 2006). When it comes to grouping students based on their learning approaches and metacognition, the picture is similarly mixed. Some students report changes in their metacognitive knowledge and regulation (in both directions), while others report no change (Balasooriya et al., 2009). Due to the eventual automation of metacognitive processes, it is no surprise that one’s awareness decreases over time, thus explaining the fluctuations in findings. It is important to note that several unrelated variables could also moderate levels of metacognition, for example, test anxiety (Harrison & Vallin, 2018).

The methodology of cross-sectional measures and between-group comparisons used in many of the studies can be problematic because they rely on assumptions about the homogeneity of groups and the stability of responses over time. (Dinsmore et al., 2018). Examining metacognition and SAL in this way risks overlooking key determining variables, such as how academic achievement changes students' approaches over time, and how learner perceptions of the situation may differ from reality (Winne & Nesbit, 2010).

Regarding the association between metacognition and academic achievement, cross-sectionally many studies have found only a weak association between the two variables, however, some findings dispute this (see Burchard & Swerdzewski, 2009, and Landine & Stuart, 1998). Nieminen, Lindblom-Ylänne, and Lonka (2004) suggest that this weak association is due to influencing aspects of the student's experience such as assessment type, time pressures, and year of academic study. For example, the researchers found first-year students showed weak to no links between their metacognition and academic achievement, whilst final-year students showed a far stronger association between the two. Longitudinally, studies have noted how the choice of learning approach interacts with metacognition and academic achievement, however, the findings on approach efficacy are mixed. According to some studies (Chen et al., 2015; Groves, 2005), there may not be a significant connection between deep learning methods and academic performance. Instead, these studies found that surface learning strategies tend to be used more frequently over time, even though they can have a negative impact on final grades. In other words, while deep learning strategies may not necessarily lead to better academic achievement, surface learning strategies can hinder academic success.

Pertaining to the longitudinal changes in the learning strategy itself, the research is again mixed (see Asikainen & Gijbels, 2017 for a comprehensive review). Some studies show increases in surface learning strategies throughout students' higher education studies (Groves, 2005; Gijbels et al., 2009; Rahman et al., 2013), whilst others note a more curvilinear relationship. Initially, surface approaches are heavily used (Platow et al., 2013), but then decline as the course progress, to only increase again at the end of the course (Choi & O'Grady 2011). This initial increase in surface learning might be in part due to the intuitional demands placed upon the students and their adjustment to higher education (Cano, 2005). Conversely, other studies find little support for any longitudinal changes in either learning approach (Reid, et al., 2005; Herington & Weaven, 2008; Wong & Lam, 2007). This finding is thought to be due to the initial anchoring/strength of the approach most frequently used by the student. As Gijbels et al., (2008) suggest the stronger the initial approach to learning, the less likely students are to change their approach over time.

To summarise, the evidence from the literature review presented above is unclear regarding longitudinal changes within SAL, the possibility of clusters within student metacognition and learning approach. It is also important to investigate the effect of metacognitive approaches on student grades to demystify this picture.

Current Study

The aim of this study is to examine the longitudinal changes in SAL and metacognition to help establish a clearer picture of specifically: i) how students develop metacognitively and

implement different learning approaches across their studies, and ii) whether either construct influences overall academic performance. Uniquely this study looks at these possible changes across a complete Psychology degree program (i.e., three years). It is hypothesised that:

> H_1: Surface learning approaches will be more prominent than deep approaches within the first semester of study.
> H_2: The type of learning approaches used by students will change as they progress through their degree, with students in later years displaying deeper than surface learning approaches.
> H_3: Students' metacognition will improve over time, as they develop greater awareness and the techniques to regulate their learning practices across their degree.
> H_4: Students clustered in the category of utilising deep learning approaches and high metacognitive functioning will have the highest overall degree grade.

Methods

Participants and Procedure

The current study took place in a research-focused university in the North-West of England. The Psychology degree course has a relatively large cohort, with around 1,400 undergraduate students across the three years of study. The data was gathered across two consecutive cohorts (2016/17–2017/18). All the participants were enrolled in the undergraduate psychology course (three years of studies). Demographically, the enrolled students are heterogeneous comprising mostly UK Caucasian females between 18–23 years old (approximately 93% of the cohort). The data collected aptly reflects the course's demographics, thus suggesting the collected samples is representative of the institution from which they were gathered. Due to their imbalances, the following factors were not explored further: biological sex, age, and nationality.

The curricula included specific compulsory modules for the first and second years to ensure that students obtain knowledge on psychology discipline and develop skills essential for their studies and future career. However, in their third-year level of studies, psychology students could select from a variety of optional modules building their year of studies based on their interest and career path that they would like to follow e.g., forensic, health, clinical and cognitive psychology. The degree programme was bps accredited and followed QAA guidelines in its development.

The recruitment process for this study started after gaining the Ethics application (Code: IHPS 396-2016; IPHS435-2016, & IPHS1369-2016) approval from the University of Liverpool. The students have been informed about this study through an email and a VLE announcement which have been posted in the first-year research methods and statistics module. First-year undergraduate students voluntarily completed the measures during an introductory statistics class in their first week of university, in 2016 providing data to form a baseline measure (n=452).

This was then followed up with a second (2016) and third (2017) wave of data collection when students of all years had the opportunity to complete the measure a second time in their lectures during weeks 4-6 in their second semester (this resulted in 140 first-year

respondents, 211 second-year participants, and 141 third-year students). Unfortunately, attrition rates were high, so only 385 students completed the measures more than once across their degrees.

Materials

Two self-report measures were used in this study: the revised two-factor study process questionnaire (R–SPQ–2F, Biggs et al., 2001) and the metacognitive awareness inventory (MAI; Schraw & Dennison, 1994). The R-SPQ-2F consists of 20 items on a five point Likert scale with two main factors and two subfactors which are deep and surface learning, and motive and strategy respectively.

The MAI consists of 52 items with the two main factors of metacognitive knowledge and metacognitive regulation. Metacognitive knowledge breaks down into three subfactors of declarative, procedural, and conditional knowledge. Metacognitive regulation comprises five theoretical components: planning, information management, monitoring, debugging, and evaluation.

Table 11

Alpha Scores for R-SPQ-2F and MAI Subscales in Full Sample

R-SPQ-2F Subscale	Alpha value	MAI subscales	Alpha value
Overall Deep	.779	Metacognitive regulation	.768
Overall Surface	.786	Metacognitive knowledge	.600

Finally, data on student performance is measured by the final grade percentage sourced from official University records, this gives a grade out of 100, with failing grades below 40, third class grades ranging between 40 and 49, 2:2 grades ranging between 50 and 59, 2:1 grades ranging between 60 and 69 and first-class grades are those of 70 and above. The overall grade is a cumulative grade of all the assessments taken throughout the Psychology course and therefore can be a proxy for the effects on learning outcomes. A small number of students (n=37) subsequently dropped out in their first semester meaning their grade data was unavailable.

Analysis

Students who completed the measure only at one-time point (n=944) were analysed using a MANOVA test to examine the effects of each of these scales on student grade (deep learning, surface learning, metacognitive knowledge, metacognitive regulation). ANOVA statistical analysis was also used to examine the general differences between year groups. Finally, a cross–lagged model then explored the differences within the individual students who completed the measures at both time points (n=385). The data was analysed using SPSS Statistics version 24 and AMOS version 24.

Results

To explore the between and within changes in student learning a series of analyses were conducted. The first analysis used the data from students who responded at a single time

point only Table 11 presents the descriptive statistics and results of the Spearman's Correlation test between the theoretical components of learning approaches (deep and surface) and metacognition knowledge and regulation.

Table 12

Spearman's Correlation for Learning Variables (N = 944)

	Mean (± SD)	Deep Learning	Surface Learning	Metacognitive Knowledge	Metacognitive Regulation
Deep Learning	29.01 (± 6.64)	-			
Surface Learning	23.29 (± 6.71)	- .433*	-		
Metacognitive Knowledge	12.25 (± 2.48)	.240*	- .211*	-	
Metacognitive Regulation	24.84 (± 5.17)	.360*	.257*	.436*	-

*p < .001

Differences Across Year of Study

A MANOVA statistical analysis explored the first hypothesis (H1) regarding the differences between the years of study and the four learning variables (two learning approaches and two metacognition components). The data for surface learning and both metacognitive components were not normally distributed and so were log transformed prior to the analysis (see Appendix).

The MANOVA showed a significant effect of the year of study [Pillai's trace = .304, F (2, 710) = 31.73, p < .001, η^2 = .152]. Significant differences between year group and metacognitive regulation, deep learning approaches and surface learning approaches were found. No significant differences were found between the year group and metacognitive knowledge. Significant findings and post hoc tests are reported below.

Metacognitive Regulation and Year

A significant effect of year and metacognitive regulation was found, F (2, 712) = 5.21, p = .006, η^2 = .014, Specifically, there was a significant difference between (i) the baseline initial measurement (24.50 ± 4.95) and year three responses (26.05 ± 4.98) (Dunnett T3, p = .003), and (ii) between years two (24.44 ± 5.67) and year three responses (Dunnett T3, p = .022).

Deep Learning and Year

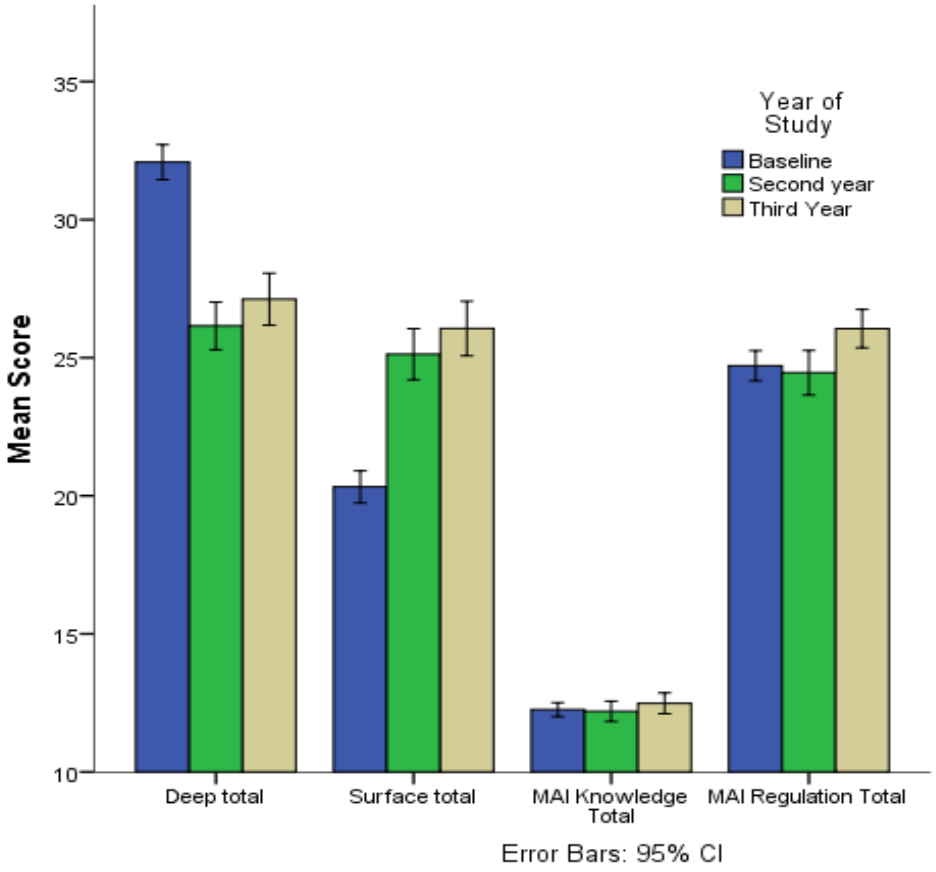
There were also significant differences between deep learning exhibited by students in different years F (2, 712) = 70.40, p < .001, η^2 = .165. Deep learning scores decreased significantly (Bonferroni p <.001) from baseline, (31.86 ± 5.75) to year two (26.23 ± 6.09) and year three (27.05 ± 6.68). However, there was no significant difference between scores in the second and third years (p = .354).

Surface Learning and Year

A similar pattern of results was found with surface learning scores, F (2, 712) = 65.52, p < .001, η^2 = .154. Scores at baseline (20.59 ± 5.43) were significantly (Bonferroni P < .001) lower than scores at year two (25.14 ± 6.57) and year three (25.94 ± 7.13). Again, there was no significant difference between scores in year two and year three (p = .548). Figure 10 illustrates the mean scores for the four variables measured in different years of study.

Figure 12

The Mean Scores with Error Bars for Learning Approaches and Metacognition Components



Differences in Assessment

The potential differences between the three years of studies (groups) based on student performance over time were analysed to test the second hypothesis (H2). A MANOVA statistical analysis based on grade boundaries (1st, 2:1, 2:2, 3rd and fail) showed a significant effect of grade [Pillai's trace = .050, F (4, 708) = 2.23, p = .003, η^2 = .012]. No significant differences were found for metacognitive factors of knowledge (F (4, 708) = 1.49, p=.611) or metacognitive regulation (F (4, 708) = 1.22, p = .698).

Significant differences between grade boundaries with both deep F (4, 708) = 5.18, p < .001, η^2 = .028 and surface learning F (4,563) 6.07, P = .034 η^2 = .011 were found. In the case of deep learning, the only significant differences identified were between students who failed (33.92 ± 8.03) and those who passed with (i) a third grade (27.59 ± 6.74), p = .013; (ii) a 2:2 grade

(28.61 ± 5.53), p= .004, (iii) a 2:1 grade (28.38 ± 6.90), p = .047, or (iv) a first grade (29.80 ± 6.60), p = .038. Conversely, in the case of surface learning, results were only significantly different at the higher grade levels between those who received grades 2:2 (24.03 ± 6.34) and first (22.31 ± 6.65), p = .038 or a 2:1 (23.89 ± 6.93) and a first, p = .002. A further analysis of the overall effect of the year was considered, however, the model was not significant (p = .164).

Clustering of Variables

Following the literature suggestions regarding the contradictory and non-significant findings on different student grade clusters, clusters were created by dividing student scores into high and low scores, using a median split. Four group clusters were created, those that were high/low on both measures and those that were high on one measure and low on the other. These were used to further explore H_2.

A one-way ANOVA showed there was no significant difference between the metacognitive clusters and grade at baseline F (3, 466) = 4.49, p = .128; at second year F (3, 466) = 1.17, p = .726; or third year F (3, 466) = 3.20, p = .086). A further one-way ANOVA examining the effect of the learning approaches and cluster group showed no significant differences between the second F (3, 466) =7.54, p = .216 and third year F (3, 466) = 1.10, p = .910 clusters. There was, however, a significant effect at the baseline cluster F (3, 466) = 7.77, p <.001 for the learning approach. Specifically, high-scoring students on both deep and surface learning approaches (57.33 ± 18.93) had significantly lower scores than (i) students with high surface and low deep scores, (65.15 ± 13.39) p <.001, or (ii) those with high deep and low surface scores, (63.62 ± 10.64) p = .017, and (iii) students whom for both scales showed low scores, (63.09 ± 18.05) p = .028.

The grades of students who completed the study more than once, (63.59 ± 8.08), were significantly higher than the grades of those who only completed the questionnaire only on one occasion, (62.17 ± 13.12). Equal variances not assumed *t* (869.54) = -2.164, p = .031. These students represented the more conscientious type, however, further paired samples t-test's show that their marks do not vary over time (year 1 to 2, p = .691; and year 2 to 3, p = .510)

Cross-Lagged Models

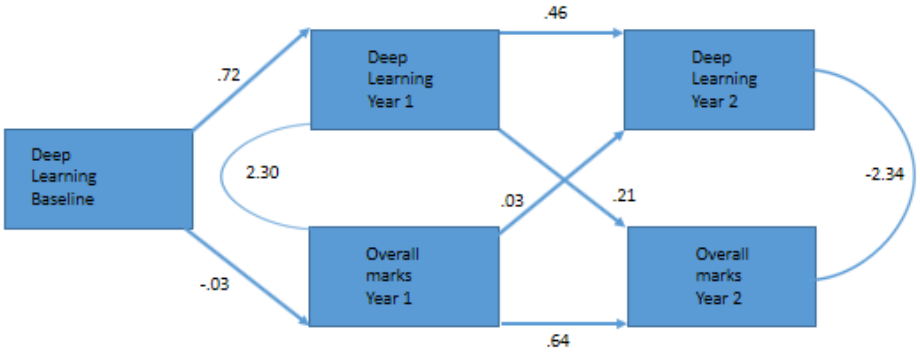
The next step looked at the longitudinal effects of each of the learning predictors on the student final grade record using a series of cross-lagged models to test the third and fourth hypothesis These models were used due to their ability to estimate autoregressive effects and examine the directionality of the relationships between the two learning concepts (Little 2013; Newsom, 2015). Full Maximum Likelihood (FML; see Enders 2001) was used to handle missing data. After establishing measurement invariance, bidirectional cross-lagged panels were used to investigate the reciprocal relationship between each of the variables in student grades.

Our results indicated that the cross–lagged model displayed a poor to adequate fit, $\chi^2 = 11.30$, p = .004, NFI = .944, CFI = .950, RMSEA = .146. Apart from the initial deep learning model, no other variables showed an association with grades over time. Specifically, the levels of deep

learning at the end of the first year significantly contributed to the overall grade for year one independently of previous learning (β = .21, SE = .09, p = .013) (see Figure 12).

Figure 13

Cross-lagged Path Model for Deep Learning Between Baseline and Year One and Two



Unfortunately, when analysing the longitudinal data, the groups were unevenly weighted, meaning that it was not possible to conduct inferential testing on this data. Descriptively, 56.9% of students presented a change in their learning between the baseline measure and year two, in either their metacognitive knowledge or regulation and/or their approach to learning. Similarly, 53.6% of students presented a change in these scores between years two and three. These changes in one variable (student learning strategies and metacognition) did not correlate with changes in the other (p = .299, years 2/3 p = .216). Where students had high initial scores in one area (e.g., metacognitive knowledge) they tended to change scores to a lesser extent than those with low initial scores in the same area.

Discussion

The aim of this study was to examine how the SAL and metacognition of Psychology students change over time. Overall, based on students' responses to the self-reported questionnaire and their grade records students' metacognitive regulation increases over time, but levels of metacognitive knowledge is not affected over the years. In the case of SAL, results show distinct changes from the initial baseline scores gathered at the start of student studies to the second semester of year 1. In the case of deep learning, there is a decrease over time whilst surface learning has a slight initial increase between the first and the second year, but it then remains relatively stable longitudinally. Both sets of changes indicated mostly a very weak or non-significant association with the final grade.

When examining the between subjects' data, no differences were found between students' levels of metacognitive knowledge and year group. However, metacognitive regulation abilities showed significant differences between years, increasing steadily from year 1 to year 3, with the steepest increase seen between years two and three. This finding aligns with Young and Fry (2008) who found changes across the metacognitive knowledge, but not across metacognitive regulation within undergraduate and postgraduate students.

Both the deep and surface learning approaches changed over the course of student studies. Surface learning increased considerably in the first year of studies and then remained steady across years two and three. Conversely, levels of deep learning decreased from the baseline to the second year of study but remained unchanged between second and third year. Equally, as identified by the correlations between metacognition and learning approaches (Table 2) there are the interconnectedness of both deep and surface approaches. However, a lack of consistent correlation is identified when examining changes over time. Although these concepts may be linked together, they may not develop at similar rates in students.

Assessment type provides one potential explanation for these changes. In the programme under investigation, first-year students were predominantly assessed using multiple-choice examinations, which typically support the adoption of a surface learning approach from students (Elliot et al., 1999). By initially presenting students with assessment types that encourage surface learning it is likely that students may continue to use this approach throughout their studies. This is likely due to the reduced time and effort needed in this approach, which by the student is still perceived to be sufficient in achieving a good academic outcome. Levels of deep learning increased (albeit non-significantly) in students within their third year, a finding which could be related to increased subject mastery and/or increased interest as the curriculum becomes malleable to the student's own interest areas through optional modules and/or the 3rd year dissertation (research project).

The large differences between student learning strategies at baseline and other time points could be explained by two interpretations. Firstly, this difference could be based on prior experiences, and limited exposure, students have to a variety of engaging teaching methods and learning approaches within their educational experiences prior to starting university (Wingate, 2007). This means that if students have not had access to a wide range of effective teaching methods and used to employ various learning approaches previously, they may struggle to adopt a new approach to adapt themselves to the demands of the new teaching methods enhancing their learning experience. For instance, if a student had a teacher who's teaching primarily relied on lectures and memorisation-based assessments, they may not be as prepared to adopt a deep learning approach or they may need more effort and time to excel in a class that requires critical thinking and problem-solving skills. On the other hand, students who had opportunities to engage in more hands-on and interactive learning experiences may be better equipped to adopt deep learning and to tackle academic challenges which are based on the higher order skills (i.e., apply and synthesise knowledge, and critical thinking; Phan, 2011). Equally, overly ambitious expectations by the students themselves regarding the learning approaches they thought they would use at university could also explain our findings. Based on the previous literature, higher education requires independent study often forcing initial plans to approach learning with deeper strategies to ones with more realistic estimates once students gain university experience and familiarise themselves with course workloads (Diseth, 2007; Murray-Harvey & Keeves, 1994). The findings of this study indicated that it was likely that the workload demands over the years may have resulted in changes to SALs. It seems that work demands increase students may engage in "satisficing" approaches (a decision-making strategy in which the individual aims for an adequate over optimal result) by investing the bare minimum time and effort needed for a task's completion (Biggs, 1993). It is possible that students who followed a surface learning to mainly factual recall information rather than to spend effort and time for deeper

learning experience as they. In general, it is easier to induce a surface approach to learning than to encourage a deep approach (Marton & Säljö, 1976; Jabarullah, & Hussain, 2019).

Regarding SALs and student grade results, it seems that failing students within the sample were perhaps overconfident in their levels of deep learning rating these higher than any other group. A potential explanation regarding this finding could be that these students may overestimate their effort wrongly thinking that they follow a deep learning approach. A potential training on how they study and reflect on knowledge to develop high order skills may assist these students (e.g., Filius et al., 2019, who used audio-based peer feedback to develop students deep learning strategies). The data also indicated that as students' grades improved over the years, they tend to rely less on superficial methods of learning. This implies that while a basic level of surface learning can be helpful in achieving a passing grade, it may not be enough to achieve higher grades. This links to Biggs' (2003) suggestion that students may be using effective strategies, but in an inconsistent or poorly conceptualised manner within their learning approaches, possibly because they are not equipped in knowing how to use such techniques effectively when first entering higher education (Wingate, 2007). The lack of change in metacognitive abilities is likely due to the high standards placed on students for entry into the course. Those severely lacking in metacognitive knowledge or regulation are unlikely to reach tertiary education (Luwel et al., 2003).

Students who completed the questionnaire more than one time point (had significantly higher grades than those who only took it once. This is perhaps not surprising since those with better engagement levels tend to be more willing to engage in such self-report inventories (Porter, et al., 2004; Neilson, et., 1978). This raises the question of how representative this sample is to the wider student cohort. This finding coupled with the evidenced changes in metacognitive regulation suggests that the changes found in this study and that of Young and Fry (2008) may be driven by more able students in the sample. These students could potentially continue within higher education whilst those lacking in good metacognition and effective deep study habits are less likely to continue, terminating their studies at the undergraduate degree level.

Viewing the sample as a whole cohort, students' directions of learning approach did not change as much as it was expected, and it has been found that effect sizes were small. The findings of this study overlook the possibility of significant changes within the subgroup level. It is possible that different groups exist within the population as suggested by Asikainen and Gijbels (2017). Indeed, when examining the between-subjects (cluster) data, at the initial baseline students who scored highly for both deep and surface learning approaches exhibited grades considerably lower than those in other clusters. One potential explanation for this finding could be that these students could be taking a sporadic study approach, using a variety of diverse approaches hoping to find out which of the two worked better each time or because the curriculum structure that the fixed modules they did not have interest in all the modules. However, by the time these students reach the end of their first year had experience with the course and assessment demands and their approaches appeared to be much more stable with most leaning marginally towards deeper learning supported.

Limitations

This study did carry with it a range of limitations. Unfortunately, the longitudinal sample was too small to effectively test for variance within student clusters due to the high attrition rate. Attrition might in part have been due to the long 80-item questionnaire. Students who completed the study at more than one-time point tended to be better performing and more engaged than the other students. As such, the lack of change seen in these students may be because of the fact they were already using successful metacognitive skills and approaches to their learning. A further explanation for the lack of this change is suggested by Richardson (2011) who noted that students tend to give similar answers across time based on their perceptions of learning. Ironically, poor metacognition means that students are more likely to report a lack of change in their views, perceptions or, even if their study habits have changed.

Another limitation was the broadness of the measures used and sample selection biases. As Yonker (2011) noted students tend to vary their learning approach according to the task. By asking at the overall course level students might have responded differently than if asked at a more granular level, such as a module or even task level. By examining these factors at a course level, students were asked to generalise their experience. However, due to immediacy effects contextual factors they would have mediated their responses on the questionnaire. For example, within the degree programme, students in their third year could pick from a choice of modules, whereas those in their first and second years could not thus driving students to have different interpretations of current tasks and assessment types creating answer variation. Indeed, as Laurillard (1997) suggested approaches to learning might be not stable characteristics but rather determined solely by student perceptions of the need for the current task. Several factors, such as perception of assessment, current workload, topic interest, and personality traits and states (e.g., mental health well-being) might also affect student responses (Bostani et al., 2014). For the student sample, the curriculum included fixed modules for the first two years, while the types of final exams were mainly multiple-answer questions. Essay-type questions, for which students should exhibit more advanced high-order skills and deep learning (i.e., critical evaluation and knowledge synthesis; Scouller, 1998), mainly support the coursework and its weight against the final grade was less than the final exams.

A third limitation is related to the self-reporting measures used. Studies examining SAL have shown that reported answers might be distinctly different to actual student behaviours (Dinsmore et al., 2008; Artelt, 2000). Students may tend to report strategies they prefer to use rather than those they do use (Samuelstuen & Bråten, 2007). Thus, it is possible that students reported their perceptions or intentions rather than their actual study habits, contributing to the lack of connection between student approaches and grades. As Groves (2005) pointed out these measures rely on student self-reporting and as such, any shift from deep to surface learning may be more closely related to a change in perceptions rather than an actual change in one's learning approach. Richardson (2004) further suggested that changes seen in the longitudinal use of self-report measures could simply be because students reconstructed their autobiographical memories of their study habits to fit implicit theories about personal change. In the case of the baseline measurements, it is likely that some students overestimated their levels of metacognitive regulation and deep learning based on the course's expectations rather than their own study habits. Just because students perceived themselves as deep learners did not mean they necessarily were (Choy et al., 2012). Students

moving from A-level study to a university degree level often adopt a deep learning strategy in the first few weeks of the course but might fail to sustain it as the workload on the course increases gradually over the years of studies (Lawless & Richardson, 2002). This trend might also reflect in the findings of this study.

Implications

This investigation's main implication suggests that teachers should promote awareness and thus better learning behaviours simply by informing students about effective problem-solving strategies and discussing cognitive and motivational characteristics of thinking (Mokhtari & Reichard, 2002) by offering relevant training to students. Along with the wider literature recommendations the findings of this study support the idea that teachers should aim to introduce students to new ideas that would prove helpful in supporting learning processes (Trowler & Bamber, 2005). Part of the challenge for teachers is how to encourage students to develop deeper approaches (Tomanek & Montplaisir, 2004). Ultimately, students' choice of learning approach will depend on a multitude of factors. These may be the result of a complex interaction between metacognitive ability, previous effectiveness of strategies used, teaching context motivation levels, and assessment type (Entwistle & McCune, 2004). The effect of each of these factors will also vary from task to task meaning a clear pattern of SALs may be difficult to identify (Fincher et al., 2006). Nonetheless, by developing a clear understanding of how students approach their learning, appropriate solutions can be recommended to students regarding their own learning process in turn improving student outcomes (Sharma, 1997).

Conclusion

This study aimed to contribute to the interesting topic of students' learning patterns in Higher Education recognising the gap in the literature (Asikainen, & Gijbels, 2017). The study's findings suggest there is a complex yet clear relationship between student learning approaches and their final grade outcomes. Students will lean towards more surface learning as their (perceived) workload increases, and assessments become more challenging. These changes vary in less abled students who show much lower levels of change compared to higher performing students, suggesting the existence of distinct clusters producing differing study behaviours and outcomes. By supporting the development of strong metacognitive abilities in students, teachers can facilitate student usage of deep learning strategies, which have a small but noticeable effect on academic achievements. Taking such action not only improves the success of a department/university but also facilitates continued student success within their studies and unlocks higher/wider opportunities upon their degree completion.

Future studies would benefit from a longer period of longitudinal measurement including how students are approaching their learning and the quality of it (Chan, 2010), as well as following students through until the end of their study. Taking such an approach would enable educational researchers to more accurately track when changes to learning approach/metacognition occur. Studies should also take place with students showcasing a wider range of abilities. The current study mostly found responses from students at the upper end of the degree profile (2:1 and above), therefore the learning patterns seen may not

accurately reflect those at the lower end who are arguably most in need of intervention to help support their learning.

6. Study Four: Diversity of Strategies for Motivation in Learning (DSML) — A New Measure for Measuring Student Academic Motivation

Abstract

Although the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich & De Grott, 1990) has been widely used to measure student motivation, researchers have raised questions regarding its length and several problematic statements. This study introduces a new questionnaire, adapting items from the MSLQ and including three new key themes of course utility, procrastination and use of diverse sources. A total of 1246 students from a university in the northwest of England, studying a range of subjects and from across all grade boundaries, completed the questionnaire. Factor analysis suggested a 24-item questionnaire, including 6 factors: test anxiety, self-efficacy, source diversity, study skills, self-regulation and course utility. The measure, Diversity of Strategies for Motivation in Learning (DSML), has good predictive power for students with or without academic successes, and it can be used as a quick and an early alert monitoring tool to measure student motivation and study skills. The DSML has supported various interventions; however, further testing is required in other cultures, languages and educational environments (such as schools and colleges).

Introduction

In a wide range of academic domains, the success of students depends heavily on their ability to envision, manipulate and navigate complex multidimensional information presented within their studies (Korhoen et al., 2019). When investigating student motivations and behaviors, there is a vast array of methods, measures and interventions from which to choose. Additionally, educators conduct most studies alongside teaching and therefore seek methods that are time-efficient and easy-to-use, -administer and -analyze. Hence, the self-report measure remains one of the most popular choices as this needs minimal input from the researcher to gather data; thus, research should directly focus on improving these measures (Schellings et al., 2011; Berger & Karabenick, 2016).

Despite drawbacks to their use (Lovelace & Brickman, 2017) self-report measures remain the most popular method of data collection and aim to tap into a range of underlying concepts. Such concepts include self-efficacy (Bandura et al., 1997); learning approach (Biggs, 1993); and self-regulation (Zimmerman, 1990), which have all been shown empirically to have a moderating effect on student outcomes (Supervía et al., 2022; Bakhtiarvand et al., 2011; Xu &

Qui, 2021; Biggs et al., 2001). Common measures used to study this phenomenon include the Revised Two Factor Study Process Questionnaire (RSPQ; Biggs et al., 2001) the Metacognitive Awareness Index (MAI; Schraw & Dennison, 1994) and the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich & de Groot, 1994). Since its development, the MSLQ has been used across various fields and types of education (Hancock et al., 2002; Rotgans & Schmidt, 2009; Broadbent, 2017) and has been cited almost 6700 times, demonstrating its popularity in the field (Google Schloar, 2022). The measure is comprised of 81 seven-point Likert scale items, measuring student behavior across 15 different subscales. Scores are then summed to produce a single score predicting student study motivations. The MSLQ consists of two primary scales—motivation and learning strategies. The motivation scale is broken down into 6 subscales of 31 items regarding goal beliefs, skills and anxiety related to tests (Laird et al., 2006). The learning strategies scale is based on 9 subscales, with 50 items assessing cognitive strategies and resource management skills (Jackson, 2018).

Despite its popularity, several issues with the measure have been identified by various scholars. Credé and Phillips' (2011) meta-analysis on the MSLQ reviewed 67 studies covering over 19,000 students and found that the MSLQ offered a large variation in its predictive ability with different subscales ranging from an effect size of 0.4 (effort regulation) to 0.05 (help-seeking). Furthermore, the authors identified items including conditional content statements (e.g., whenever X occurs, I do Y) as being prone to issues regarding their interpretation and clarity (Whitebread et al., 2019). Similarly, ideal point items carry a similar critique in which interpretation and response vary depending on the student's successes (Cho & Summers, 2012). For example, the item "I ask the instructor to clarify concepts I don't understand well" is likely to be answered positively by middle-performing students and negatively by both high- and low-performing students, albeit for different reasons. High-performing students would not need clarification while low-performing students would not seek help due to either not realizing they had misunderstood or not bothering to clarify unclear points.

Another substantial critique of MSLQ is its incorrect assumption that students are heterogeneous across courses and institutions (Richardson, 2004). Students are, in fact, remarkably diverse, displaying variation across their outcome grades, motivation and learning approaches. Through the measure's transferability (i.e., its use across course types), distinct nuance and course specific factors are not accounted for, which may play a significant part in student motivation and behavior. Additionally, factors, such as one's psychological state, social networks, support, environment/contextual setting, and SES background, will also have a significant relationship (whether that be main or mediating) on student motivation. For example, the disparity between lower and higher SES backgrounds on academic student achievement is well-documented (Hernandez et al., 2021), with higher SES students often attaining higher grades through having access to a wider range of higher-quality schools and additional resources and support (e.g., private tutors). As such, Winne and Baker (2013) suggested that multilevel cross-validation (a method for assessing the effectiveness of prediction models that involves frequent training and model testing across data subsets) is necessary to combat the above critique before the use of existing self-reporting measures. Issues with the MSLQ's factor structure have also been noted, leading Dunn et al. (2012) to suggest the reconsideration and restructuring of the metacognitive, self-regulation and effort regulation items. Hilpert and colleagues (2013) additionally proposed that the extrinsic goal orientation items should be re-examined due to their ambiguity with several other

researchers supportive of this point (Jackson, 2018; Griese et al., 2015; Khosim & Awang, 2020).

It is worth noting that Pintrich and colleagues' (1991) original MSLQ measure was based on a single sample and following a confirmatory factor analysis conducted by Muis et al., (2007), it has been suggested that the factor structure was not as stable as initially suggested. Upon this finding, it is suggested that the use findings from the MSLQ be interpreted with care if indeed used. This warning point was also echoed by Gable (1998) who suggested that diverse samples of students were necessary to establish the validity of the factor structure.

Additionally, another area of the critique of the MSLQ is related to the current diversity of educational methods and settings (i.e., the utilization of a range of online tools by contemporary students and/or on-campus teaching), while Pintrich et al's (1991) original student sample was confined to traditional teaching methods and customs used in the 1980s and 90s. Specifically, in the past 30 years, shifts in both teaching practices and the use of technology have vastly changed education (Limniou et al., 2021). Teaching practices have developed considerably with more use of student-centered teaching practices and an increasing emphasis on the value of formative assessments (Dunn et al., 2012; Baverl, 2022). Similarly, technological modifications have changed how students access and use a range of learning materials, e.g., accessing online journal articles rather than visiting libraries. This multifaceted and ever-increasing role of technology in education makes it inevitable that many of the original MSLQ questions have diminished in their relevancy. Indeed, when Cho and Summers (2012) conducted an analysis of the MSLQ in an online learning environment, they found it to be a poor fit, with many of the items no longer appropriate to student learning experiences. The authors suggested that current researchers consider adapting the measure to better fit current students' situations. These changes within the educational sector make it inevitable that some MSLQ items need adapting to reflect contemporary student learning conditions.

As well as implementing the changes seen in current study methods, the measure's theoretical basis should also be examined. Many learning inventories are developed top-down using theoretical constructs from cognitive psychology; so, as our knowledge of these constructs develops, so should the methodologies for researching learning approaches (Biggs et al., 2001; Valverde-Berrocoso et al., 2020). For example, deep learning strategies include effort regulation, time management and metacognitive ability, all of which have been shown to strongly correlate with student GPA (Richardson et al., 2012; Saele et al., 2017; Isik et al., 2018). Equally, negative correlations between study habits and grades have been found due to test anxiety (Seipp, 1991; Ali & Anwar, 2021), boredom (Pekrun et al., 2014), and procrastination (Wolters, 2003; Yamada et al., 2015; Goda et al., 2009). While the original MSLQ manual provides correlations with student grades, it unfortunately does not specify which of these were significant.

In addition to these issues in question, it is also important to consider the issue of data collection/the questionnaire structure itself. The full MSLQ contains 15 separate subscales and a total of 81 questions, taking between 20 and 30 min to administer. This can lead to respondents potentially developing survey fatigue (Kemper et al., 2019), responding without reading the question properly or even dropping out of the study, resulting in a reduction in

the quality of the data (Credé et al., 2012). The lengthier the inventory, both theoretically and practically, the higher the respondent burden. By increasing the time and effort required to complete a measure, response rates and data quality lessen due to students being less likely to provide thoughtful and considered responses. The resultant, and anticipated, poor quality data will likely make staff reluctant to use the MSLQ due to resource and complexity reasons. Conversely, shorter measures use less time and resources and offer increased flexibility for inclusion in larger surveys, or interventions, allowing researchers to adapt their data collection strategy to the needs of their study. While it is possible to use the MSLQ's subscales individually, confusion as to which subscale is most relevant to the researcher arises, creating a trade-off between resource and psychometric quality (Levy, 1968). Having said this, scale validity and reliability do not necessarily increase proportionately alongside the increase in items (Niemi et al., 1986).

The Current Study

A pilot study conducted by the current authors running the original MSLQ on 181 University of Liverpool students found that both peer learning and the help-seeking scale had low alpha coefficients and poor internal consistency. These results were found to be consistent with both the measure's authors and the results from more contemporary scholars (Cho & Summers, 2012). There were also several further issues with the data, such as weak predictive power and extensive evidence of survey fatigue (such as careless and incomplete responses). Therefore, this study aims to utilize previous research to develop a shorter and more focused questionnaire on student motivation. Following the previous studies and literature discussed recommendations, the objective of this study is to create an accurate questionnaire, targeting important but currently missing theoretical, conceptual elements while simultaneously being quicker and easier to administer than the original measure in order to reduce questionnaire fatigue (Griese et al., 2015). Another objective of this study is to develop a revised shortened questionnaire suitable for use in modern educational environments that blended learning offers. Finally, this study's objective is to include items that provide a more holistic view of student learning, such as the surface learning approach (Biggs, 1993), self-efficacy (Bandura et al., 1997), and self-regulation (Zimmerman, 1990).

Methodology

Questionnaire Development

Based on the findings and critiques discussed above, the initial step taken in developing a new measure of student behavior was to examine each of the original MSLQ items to establish which should be retained and which had poor discriminate values (Smith & Chen, 2007). As mentioned above, help-seeking and peer support scales showed a lack of consistency and were removed completely in this initial step; the remaining 74 questions were then individually reviewed. Any question which contained more than one concept was reworded and simplified. For example, question 16: "In a class like this, I prefer course material that arouses my curiosity even if it is difficult to learn" was reworded to "I like material that really challenges me even if it is difficult to learn". Further questions were also eliminated on an individual basis when it was not possible to re-word, for example, question 31: "Considering

the difficulty of this course, the teacher, and my skills, I think I will do well in this class". This question asks students to weigh out three different things and then decide on a suitable option—something which will inevitably lead to different interpretations between different students; so, it was therefore deleted. Finally, some questions were combined such as question 59: "I memorize keywords to remind me of important concepts in this class" and question 72 "I make lists of important items for this course and memories the list" into "I make lists of important terms or keywords for the course and memorize them". This process resulted in retaining 46 questions from the original measure, with 7 containing the original wording (as they were shown to have good discriminative validation in the pilot study), 8 with minor word modifications and 31 questions with amended wording. The decision to also include six questions from other measures was informed by previous findings from the study's author Hands & Limniou (2023) and the highlighted critique aforementioned in the literature review. The six questions were one from Schraw and Denison's (1994) metacognitive awareness index (MAI) and three from Briggs and colleagues' (2001) revised study process questionnaire (R2F-SPQ). As suggested by Credé and Phillips (2011), and alongside our own insights, some additional questions were written to address aspects of student motivations and behaviors that were not considered within the original measure. These included questions covering concepts, such as procrastination, locus of control and student use of digital materials. The process of removing and rewording the MSLQ items, along with adding additional questions from other measures, led to the creation of the novel measure — strategies for motivation in learning DSML.

This initial iteration was then subject to five rounds of revision and review by four educational psychology academics (see acknowledgements). These experts were invited to review the wording of the questions, suggest any potential rewording, identify semantic changes in the question meaning, and point out any errors. This process resulted in some further wording changes and question adjustments to ensure they were sufficiently discriminative to identify differences in student approach. These steps resulted in a final 64-item measure suitable for exploratory factor analysis.

In addition to the 64 questions mentioned above, two free text boxes were provided for student feedback regarding question clarity and any missed areas of assessing their learning behaviors. Students were given the option to either use a dummy or their real ID, if comfortable, to enable the linking of responses to student grades. Finally, the questionnaire asked five demographic questions on one's predicted grade boundary, year of study, the student's affiliated department, location of home country and sex. Two further questions (see Appendix 3 were included to check the validity of the answers given. In instances where the items referred to paper-based materials, these were reworded to include the appropriate digital aspects. Additionally, some terminology varied across different departments within the University; therefore, minor adjustments were made to the wording to make this clear to the students, for example, including the terms tutor or academic advisor. The finalized questionnaire (see Appendix 3) received ethical approval from the University's ethical board.

Participants and Procedure

The size of the study's sample was based on an estimate of around 10–15 students per item, determined by the recommendations of Comery and Lee (1992) and Fabrigar et al., (1999). This value was chosen to ensure that both the Exploratory Factor Analysis (EFA) and

Confirmatory Factor Analysis (CFA) had sufficient power to assess a robust model of the DSML. Data was collected in April and May of 2018, using a mixture of opportunity and snowball sampling at the University. Recruitment took place in a range of academic and study spaces across the campus (including but not limited to lectures, seminars, the library, etc.). The participants could complete the questionnaire either online or on paper. A participant information sheet was provided to the students followed by a consent form. Only if students agreed to participate in the study was the questionnaire (see Appendix 3) then administered (with an average response time of 15 min). Finally, students were debriefed and provided with a £1 shopping voucher for their participation.

Initially, 1246 responses were collected; 20 responses were removed due to incomplete or contained improper responses (e.g., rating all items the same), leaving 1126 fully completed questionnaires. The data for the initial measure was gathered in several ways. First-year psychology students were invited to complete the questionnaire for course credits (obtaining 264 respondents); second-year students also collected data as part of a course project obtaining 96 responses (these were recruited from second and third-year psychology students); and 77 students from life sciences were recruited following an announcement across two lectures. Finally, the bulk of responses (689) were collected through opportunity and snowball sampling across a variety of locations on campus. Faculty breakdown is slightly overrepresented by the School of Psychology and the Faculty of Humanity and Social Sciences, due to data collection locations being based on these corresponding Faculty's campuses (see Table 13).

The breakdown of years and grades was representative of the University's population (as shown in Tables 14 and 15). Most participants were students from the UK (91.3%), with 4.5% from Europe, 2.2% from Asia and 2% from elsewhere in the world. The sample predominantly identified as female (70.4%), with 24.8% identifying as male, 0.7% identifying as other, 2.8% preferring not to answer and 1.5% providing no response.

From the initial 1126 questionnaires, 124 participants were removed for an assortment of reasons: 8 missed both validation questions; 77 answered incorrectly on Question 41 "For this question please select: Not at all true of me"; and 39 gave a rating of three or below for Question 66 "My answers are a fair reflection of my true feelings". In turn, the final number of responses used was 1021.

Table 13

Breakdown of responses based on discipline (N = 1087)

Topic/Faculty	*n*	Percentage (%)
School of Psychology*	382	33.9
Faculty of Health and Life Sciences	189	16.8
Faculty of Science and Engineering	140	12.6
Faculty of Humanities and Social Sciences	312	27.7
School of Medicine	52	4.6
Other	12	1.1

*Psychology falls under Health and Life sciences but is provided separately as this received the most responses

Table 14

Breakdown of Students' Self-Reported Predicted Grades (N = 1111)

Grade	*n*	Percentage (%)
First class (71–100)	149	13.4
2:1 class (60–69)	628	56.5
2:2 class (50–59)	228	20.5
Third class (40–49)	28	2.5
Failing grade (below 40)	3	0.3
Unable to estimate	75	6.8

Table 15

Breakdown of the Year of Studies (N = 1115)

Year of Study	*n*	Percentage (%)
First-year undergraduate	553	49.1
Second-year undergraduate	307	27.3
Third-year undergraduate	164	14.7
Post-taught students (Master's)	73	6.5
Postgraduate research students (PhD)	17	1.5
Postdoc staff	1	0.1

Results

The factor analysis approach method has been widely used to evaluate relationships with visible variables or a set of factors by measuring an item or question. Factor analysis involves a series of statistical analyses that employ a similar and functional method instead of a single statistical method (Beavers et al., 2013). There are two main types of factor analysis EFA and CFA. Both aim to create relationships observed in groups composed of a small number of members with only a few hidden variables. However, EFA and CFA often vary in terms of the number and type of instructions and the size of the hidden variables (Brown et al., 2012). EFA is frequently utilized in the early phases of scale development and construct validation, while CFA is implemented in later phases when the underlying structure has been established based on empirical and theoretical grounds (Brown et al., 2012). As the aim of this study was to develop a new questionnaire for student motivation, EFA was implemented to test the validation of the questionnaire, whilst CFA was employed to establish the theoretical factors. Since structural equation modelling is based on the significance of differences in the covariance matrix, Yeşilyurt (2013) suggested that the number of participants should exceed the number needed for each entry in the matrix when such models are built. Participant responses were then randomly allocated into two groups — 559 responses were used for the EFA, and 462 responses were used for the CFA. The uneven splitting of the groups was justified due to missing data in the not Missing Completely at Random (MCAR) responses being deemed sufficiently large and representative of the population of interest. The data were analyzed with R 3.5.2 (published by the R project December, 2018) using the Lavaan, Tidyverse and Psych packages. Data were analyzed using an unweighted least squares (ULS) regression. Due to the ordinal structure of the data and our consideration to not make assumptions about the item distributions, this method of analysis was chosen. ULS methodology is best employed when the variances of observed variables are similar (Ogasawara, 2003). As it was likely that the items in the questionnaire were correlated, an oblimin rotation was used (Gorsuch, 1983).

Exploratory Factor Analysis Results (N = 559)

The primary goal of EFA is to arrive at a more concise and conceptual understanding of one's set of measured variables (Preacher et al., 2013). This is determined by the number and nature of common factors required to fit the pattern of correlation among the observed variables (Beavers et al., 2013).

Firstly, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy for the initial exploratory factor analysis were run, producing results ranging from 0.81 to 0.88. A value closer to 1 indicates the patterns of correlations are compact, and therefore, factor analysis should yield distinct and reliable factors—producing hopeful findings for our data. Next, we ran Bartlett's test of Sphericity to check the correlations between the variables. At all steps, the test was significant indicating that the correlation matrix significantly differed from an identity matrix denoting significant correlations between some of the variables within the measure—meeting this factor analysis prerequisite. According to Hays et al., (1998) factor loadings that exceed 0.40 are generally considered meaningful. We deleted any items with absolute values greater than 0.35 on more than one factor and any discrepancies between cross-loadings with an absolute value of less than 1.5. Each factor also had to have a minimum of three items (Pett et al., 2003). In order to evaluate model-fit we used the criteria recommended by Hu & Bentler (1999) suggesting a comparative fit index (CFI) and the Tucker Lewis index (TLI) score of being

greater than 0.90 and 0.95, respectively, for good and great fittings models. We also used a root mean square error approximation (RMSA) of less than 0.60 as indicating good model fit. Data was examined through several iterations with redundant items removed at each step (see Table 16).

In total, 40 items were removed from the scale due to either not or ambiguously loading (i.e., not loading strongly) onto any factor. The final model demonstrated a 6-factor good fit solution, with eigenvalues ranging from 2.38 (factor 1) to 1.45 (factor 5). Table 17 outlines the final model's fit statistics, whilst Table 18 illustrates the item loadings and variance percentages explained by the model.

Table 16

EFA Steps

EFA Step	Initial Suggested Factors	KMO	Items Removed
1	11	0.88	28
2	8	0.83	6
3	8	0.83	1
4	8	0.83	1
5	7	0.81	1
6	7	0.82	2
7	6	0.82	1

Note. Bartlett's test of Sphericity was significant at all steps ($p > 0.001$)

Table 17

Final Model Item Loadings and Variance Scores

Factor	Contained Items	Model Variance (%)
1. Self-Regulation	7	22
2. Test Anxiety	4	18
3. Self-Efficacy	4	16
4. Source Diversity	3	16
5. Course Utility	3	15
6. Study Strategies	4	13
Total (final model)	25	45

Table 18

Model fit statistics for EFA

RMSEA	90% CI Lower	90% CI Upper	TLI	χ^2	df	*p*
0.045	0.038	0.005	0.916	4384.66	147	< 0.001

Confirmatory Factor Analysis Results (n = 461)

While EFA is not based on apriori theory, CFA is, and thus is typically driven by theoretical expectations regarding the structure of the data (Justicia et al., 2008). The focus of CFA is on how well the measurement model, which operationalizes the theoretical factor structure, fits the empirical data derived from the questionnaire responses. This is frequently assessed using absolute indices, such as the CFI or TLI.

CFA was run using the Lavaan package in R, with unweighted least squares regression models being the most appropriate model type to use due to the data's ordinal nature and the apparent clustering seen around point 4 on the 7-point Likert response scales. The CFA model used the factors derived from the EFA, with the model showing a good fit (see Table 19) and explained 47% of the model variance.

Figure 14

Item factor loadings and the inter-correlations between the factors; the strongest loadings are apparent for test anxiety, source diversity and course utility

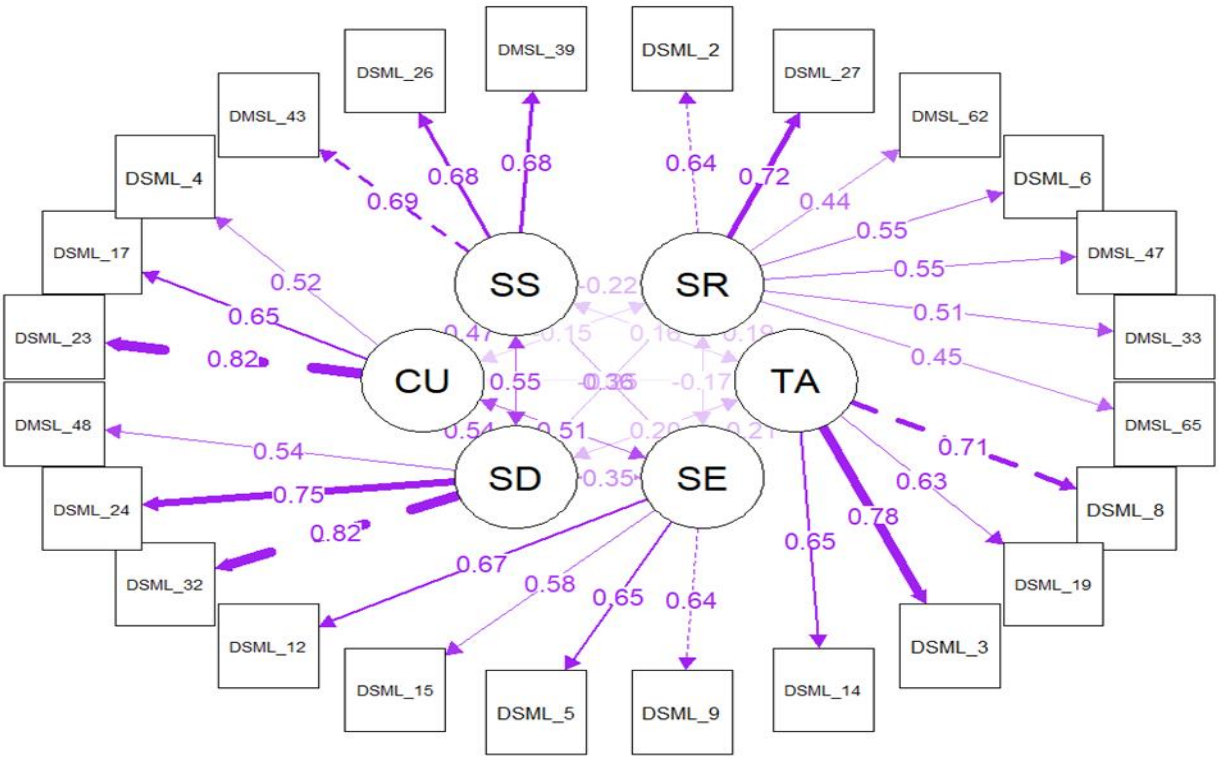


Table 19

Model Fit Statistics for CFA using Standard and Robust Modelling

	RMSEA	90% CI Lower	90% CI Upper	TLI	CFI	χ^2	df	*p*
Standard	0.129	0.124	0.135	0.905	0.918	1808.11	237	< 0.001
Robust	0.040	0.033	0.047	0.883	0.900	390.230	237	< 0.001

CFA Results and Grade Boundaries

As well as determining the factor structure, we also explored its effects on student grade boundaries. Note, the data collected on students' self-reported grade boundaries (measured on a 5-point Likert scale) showed a moderate correlation with the overall grade for the subset of Psychology students, of whom the only overall grades were available for (rs (342) 0.573, p = 0.003). This result suggests that, within Psychology, students self-reported grades were a good proxy for student performance. As Table 20 shows, the measure's factors not only correlated strongly to each other but also to student grades.

Table 20

Spearman's Correlation Matrix Between Factors and Self-Reported Grade Boundaries

Factor (*n*)	M (± SD)	Grade	Self-efficacy	Self-regulation	Study skills	Test anxiety	Source Diversity	Course utility
Grade (945)	3.87 (± 0.70)	-	0.445** (*n* = 931)	0.199** (*n* = 917)	0.730* (*n* = 992)	−0.105* (*n* = 888)	0.196** (*n* = 939)	0.140** (*n* = 934)
Self-efficacy (1006)	4.95 (± 0.93)		-	0.147** (*n* = 977)	0.208** (*n* = 992)	−0.158** (*n* = 948)	0.273** (*n* = 998)	0.367** (*n* = 995)
Self-regulation (992)	4.47 (± 1.09)			-	0.158** (*n* = 980)	−0.143** (*n* = 937)	0.196** (*n* = 985)	0.132** (*n* = 979)
Study skills (1007)	5.31 (± 1.09)				-	0.174** (*n* = 950)	0.428** (*n* = 1000)	0.339** (*n* = 994)
Test anxiety (962)	5.09 (± 1.20)					-	0.122* (*n* = 954)	0.069 (*n* = 950)
Source Diversity (1023)	5.24 (± 1.13)						-	0.422** (*n* = 1000)
Course utility (1008)	5.60 (± 1.01)							-

*p > 0.005, ** p > 0.001

Discussion

The current study aimed to develop a short measure examining student motivations to support blended learning along with statements of higher clarity compared to the MSLQ. As such, the Diversity of Strategies for Motivation in Learning (DSML) questionnaire consists of six factors measuring self-regulation, self-efficacy, source diversity, study strategies, test anxiety and course utility. This structure was affirmed by CFA following the EFA analysis. The final resulting measure contained 3 questions that are unchanged from the original MSLQ; 4 that were subject to minor wording changes; 14 that were based on the original measure but completely reworded; and lastly, 3 newly developed questions (all of which loaded onto the self-regulation factor).

Both self-regulation and self-efficacy are key performance factors and are linked to successful outcomes (Richardson et al, 2012). Self-efficacy tends to become less helpful at explaining variations in grades as a course progresses — a finding that is particularly pronounced in lower-performing students (Kitsantas et al., 2008). On the other hand, high-achieving students tend to increase their levels of self-efficacy, further improving performance by reinforcing helpful study strategies (Zusho et al., 2003). It is suggested that the divergence in both self-efficacy and self-regulation could be due to lower-achieving students overestimating their abilities (Dörrenbächer & Perels, 2016). Furthermore, when combined with a lack of metacognitive abilities, it suggests these students are less likely to learn from previous experiences and to use this to regulate their behavior (Soemantri et al., 2018). Successful self-regulation, self-efficacy and metacognitive ability are typically mediated through students' learning behaviors (Duncan & McKeachie, 2005). It has been suggested that test anxiety mediates the relationship between self-efficacy/self-regulation and study behaviors (Pintrich & de Groot, 1990).

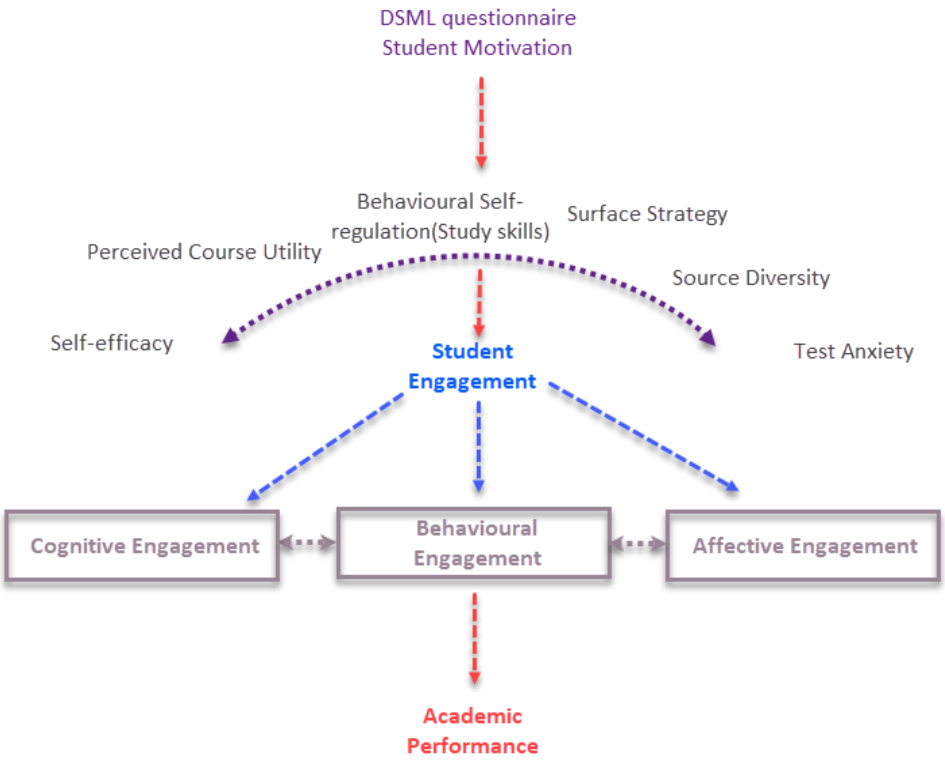
Study strategies (i.e., surface learning) and source diversity are interrelated as they reflect how students approach their studies and demonstrate their regulatory and efficacy skills; in addition, source diversity aims to recognize students who learn strategically and possess these skills. Students' behavioral self-regulation is also worthy of close attention due to the distinctiveness of this learning style (Shea & Bidjerano, 2010). Course utility relates to external motivations (personal, professional and future study) for engaging in studying, offering an explanation for why students engage in particular tasks (Laird et al., 2006).

Finally, the results of the study indicate that test anxiety is a separate and distinct factor that loads onto its factor, indicating that there is a subgroup of students who experience concerns over exams that are not necessarily related to their study strategies, self-regulation or levels of self-efficacy. This finding highlights the importance of recognizing and addressing test anxiety in students, as it may have a significant impact on their academic performance and overall well-being. By identifying this subgroup of students and providing them with targeted support, educators and mental health professionals can help to alleviate the negative effects of test anxiety and to support these students in achieving academic success. This study aimed to produce a shorter, more focused measure that addressed the key elements of student motivation and performance.

The six key elements of the DSML questionnaire are connected to student engagement and academic performance (Figure 14). Although many researchers have confused motivation with student engagement, student engagement arises from motivation (Martin, 2012; Senior et al., 2018). As student engagement is highly related to motivation, the six elements that emerge from this study could be blended with the most widely used student engagement frameworks that support cognitive, affective and behavioral dimensions (Bowden et al., 2021). The proposed short questionnaire could support studies on student engagement and academic performance, such as a recent study on the COVID-19 pandemic (Limniou et al., 2022).

Figure 15

The six component elements of DSML measuring the three dimensions of the student engagement framework that theoretically predict student performance



Taken together, these six factors combine to offer a snapshot of student behaviors and motivations that can be used to assess student behavior demonstrating both one's "will and skill" (Pintrich & de Groot, 1990). Likely, the cognitive and affective elements (self-efficacy, self-regulation, learning strategies and test anxiety) will be less affected by variations in subject domains (Rotgans & Schmidt, 2009), while study behaviors (source diversity and study skills) are more likely to be affected by specific situations and contexts (Entwistle & McCune, 2004).

While the proposed DSML questionnaire has addressed some of the issues inherent in the original MSLQ, there are still further areas for improvement. For example, although this measure has been tested in several educational research settings, it has mainly included

participants from the same UK University. Outside of the UK, so far the DSML has been only used to support an intervention in the Kingdom of Saudi Arabia (Alsharif & Limniou, 2020); thus, further work on this area is required to explore whether this questionnaire could measure student motivation across both national and international levels. Another limitation is regarding its use in various learning environments. A study conducted during the COVID-19 pandemic has explored the difference in various learning environments by using the DSML questionnaire subscale of study skills to link student motivation and engagement with academic performance (Limniou et al., 2022). An effective measure will be sensitive to the ability levels of respondents and should reliably measure different populations in a variety of contexts (Jackson, 2018). Thus, future work could further support the validation process of this questionnaire where educational researchers from different countries could test the short DSML measure in various learning environments. As with most self-report measures, a limitation of this measure is that participants need to engage in the processes of question interpretation, relevant event recall and mapping responses onto the scale options (Tourangeau et al., 2000). As such, future researchers may also consider using a fully labeled scale (with a description for every point) to reduce the ambiguities in scale interpretation by the participants (Batteson et al., 2014). In addition, another limitation is related to the level of use that could also influence the validity and reliability of the data collected. For instance, if a participant reports using an approach or strategy infrequently, their responses may not accurately reflect their actual experiences or perceptions. Similarly, if a participant reports using an approach or strategy excessively, their responses may be biased or unreliable. Therefore, it is important for researchers, in the future, to consider the level of the task the measure is addressing and to take account of this when interpreting their findings.

The DSML was developed for use at the course level (Duncan & McKeachie, 2005), however, further testing is needed to see whether this would be suitable for use at the topic or task levels (Rotgans & Schmidt, 2009; Credé & Phillips, 2011), which may shed light on some of the score variations across student groups (Broadbent, 2017; Meijs et al., 2019). Students have generalized ways of studying that they have reported in line with the current measure; however, as Hardwin et al., (2001) point out, learning styles can fluctuate in response to context variations. Attention must also be directed towards further efforts to ensure that future iterations of the measure are culturally suitable for measuring student motivations across a range of students from differing institutions, topics, cultures and languages (Jackson, 2018; Eaves, 2011; Ilker, 2014) Additionally, it may also be worth investigating the predictive validity of the measure, both in terms of grade prediction and student dropouts. We suggest the measure could be used to identify at-risk students earlier on in their studies (Credé & Phillips, 2011) by detecting changes in behavior or maladaptive learning strategies (Zusho & Pintrich, 2003). Along with assessing the predictability of the measure at the individual level, we propose that the DSML may be used to test wider disruptions at the societal level, too. For example, testing whether events creating large-scale disruptions to the higher education system, such as the COVID-19 pandemic (Limniou et al., 2021) or national teaching strikes (Hands & Limniou, 2023) have uniquely driven further changes in student behaviors. The DSML has also been used to test students' academic performance from three different disciplines when they brought their own devices to a lecture theater (Limniou et al., 2020). Therefore, the measure should be re-validated to take into account changes in the educational landscape, such as the move to online testing, which has considerably reduced student test anxiety (Stowell & Bennett, 2010; Ewell et al., 2022). It should also examine whether closely

related questions, such as those pertaining to source diversity could be aptly measured by a single item e.g., "I use a variety of sources", thus further improving the measure's speed of administration and longitudinal uses to detect changes in students' motivations. Finally, it is important to note that the currently developed model only explains around one-half of the total variance—a finding likely explained in part by the influence of background factors (Schellings & Van Hout-Wolters, 2011), the measurement of general dispositions rather than actual processes (Richardson, 2004; Heikkilä & Lonka, 2006) and on subjective judgments of one's own competence (Shea & Bidjerano, 2010; Veenman, 2011). In turn, it may be worthwhile for future researchers to triangulate the DSML data with other data sources (both qualitative and quantitative) to establish the stability and fluctuations in behaviors because of such background factors.

The DSML has been developed and designed for university students; however, many of the learning processes it taps into, such as self-regulation and test anxiety, are common to students across education. Therefore, it would be worthwhile testing the DSML in a variety of educational domains such as compulsory schooling, further education and workplace learning. Teachers could use the measure to specifically target interventions for students at risk of disengagement or experiencing test anxiety. Educational researchers could use the measure to assess the effects of structured interventions or unplanned events (such as pandemics and strikes disrupting learning), as well as to measure how these concepts change in students over time.

Conclusions

In conclusion, the newly proposed DSML measure has been tested for reliability, validity, and uni-dimensionality through both exploratory and confirmatory factor analyses. Research findings confirmed that six factors in three dimensions provided a wide-ranging overview of student thoughts, motivations and behaviors. The 24-item questionnaire provides a valid and reliable measuring scale for universities to utilize to help measure student learning behaviors, predict outcomes and design tailored interventions for low-performing students. In the current environment and landscape of higher education, having indexes measuring and reflecting contemporary student practices is imperative in order to accurately assess modern-day student behaviors and to encourage better overall practices. The development of a valid and reliable measuring scale for student learning behaviors is a crucial step in improving the quality of education and in supporting the success of all students, particularly those who may be struggling. By using this index to identify areas where students may be struggling and providing tailored interventions and support, universities and further education colleges can foster a more supportive and effective learning environment that meets the needs of today's diverse student population.

7. Study Five: Expectations and Reflections about Starting University - a Qualitative Focus Group Study with First and Third-Year Psychology Students

Abstract

The transition to University is a period of change that involves multiple transitions, educationally, socially, and emotionally. As students move from strictly regulated school environments to the relative independence of University study, they arrive with expectations of University life. For some expectations of University will not change across the course of their degree, while in others partial or even total expectation shifts may occur. The current study conducted nine focus groups with a total of 46 undergraduate students (32 first and 14 third years). It seeks to explore the academic factors that shape student experience across their degree. Using thematic analysis the study identified five main themes: prior experience, adjustment to university, staff relationships, the experience of studying, and future plans. Together these show how students' expectations change across the course of their degree. We suggest that good expectation management for students' first starting University would help the initial transition. Additionally smaller transition support such as between modules coupled with more employability support across their studies would be beneficial for students' experience across their degree. Findings also highlight the important role played by staff in developing a feeling of belongingness.

Introduction

When students decide to attend a University they may have particular expectations about the program they have selected including the type of topics they will cover and the teaching they will get (Briggs, 2006; Hassel & Ridout, 2017; Money et al., 2017). The progression from secondary to higher education is a period of change characterised by multiple concurrent transitions, involving several contextual and environmental changes such as geographical, educational, and living (Gall et al., 2011; Holton, 2015). This period also involves various interpersonal transitions leading to changes in areas such as friendship, levels of independence, and self-perceptions**.** Although many researchers have explored the transitional period from college to university, further research is required in order to avoid so-called "blanket statements" regarding student expectations (Nadelson et al., 2013), not all expectations are the same and different students will come with a variety of expectations based on their previous environments and experiences.

Depending on their background, prior qualifications, and previous experiences students will undergo their educational transition in different forms and intensities, however, as Jackson (2010) notes, for almost all students this period will represent one of disequilibrium. Typically, this is illustrated by a U-shaped period of adjustment. The novelty of the new experience in the first few weeks brings excitement and enjoyment, followed by a period of disillusionment and dejection (which can induce dropping out for some), lastly followed by a period of

adjustment (Risquez et al., 2008; Menzies & Baron, 2014; Jaremka et al., 2020). In particular, students who have unrealistic academic expectations (Cook & Lecky, 1999; Denovan & Macaskill, 2013) tend to gain lower first-year grades than students who have lower or more realistic expectations of their academic abilities (Smith & Wertlieb, 2005). The first semester in particular is seen as a key stage in the student's transition cycle as this is when they are most likely to drop out of university or disengage with their studies (Bolam & Dodgson, 2003). These risks are even higher for students from non-traditional or widening participation backgrounds who face additional challenges, such as those with a disability (Kilpatrick et al., 2016), or international students (Ecochard & Fotheringham, 2017).

As well as navigating the personal challenges of higher education such as financial pressures (Hoffman et al., 2008), making friends (Chiang, 2007), and homesickness (Maunder, 2018; English et al., 2017), students also have to deal with academic challenges and changes that could affect their study outcomes. Factors such as prior study (Hands & Limniou, 2022) and transferable skills from prior academic and vocational experience (Schaeper, 2020) have been shown to affect the expectations of students arriving at university. Furthermore, factors such as engagement with learning (Kuh et al., 2009), self-efficacy (Bandura, 1994), and self-regulation (Zimmerman, 2000) are also known to impact student learning experiences once at university. Additionally, even the structural environment such as the use of a Virtual Learning Environment' (VLE; Hands & Limniou, 2023), or lecture recordings (Nordmann et al., 2019) can impact student experiences. In essence, students face a range of barriers and facilitators to their learning which are multifaceted and multi-dimensional. This complex interaction inevitably has an impact on how students feel as they pursue their degrees (Nadelson et al., 2013), as well as dropout risk, future engagement, and academic success. In order to facilitate successful student transitions amidst the challenges they face student expectations must be recognised.

It is not uncommon for student study expectations to vary considerably from the reality of their university experience (McInnis et al., 2000). Additionally, these expectations can play a role in how students react to situations at different points in their academic journey. The immediacy of one's experience may change the emphasis placed on factors affecting their learning experience. For example, if asked about exam stress students will often emphasise anxiety, pressure, and nervousness prior to the exam, however, once the exam is completed, they may emphasise relief and feelings of accomplishment, disappointment, and/or regret depending on their perceived performance (Krispenz et al., 2019). The same is also true for wider student experiences. A time lapse may be necessary across a student's course of study to allow them to reflect on and fully appreciate the relevance of course activities. For example, Drew (2001) found classes aimed at developing study skills were identified as more valuable to students in retrospect vs at the time of their current engagement. Baloo (2018) points out that often new admissions students are unable to differentiate between their expectations and aspirations. As such, the expectations displayed by students may really represent socially desirable views or legitimate university objectives like career goals or academic interests. Therefore, it's important to consider both the expectations of new students and the reflections of those who have now completed their studies. The current study seeks to explore students' academic learning experiences of transitioning to higher education by comparing views from both the start and end of students' academic journeys.

Based on the prior literature, the study has two objectives. The first is to examine what aspects of students' transitions through university are initially most important to them and how such factors evolve or change as students' progress through their degree program. The second objective focuses on identifying how such factors differ among students and how they are affected by different demographic or background variables. Ultimately, this study seeks to identify and explore the key academic factors that influence student experiences of transitioning to University, and how such factors change over one's degree program.

Methods

This study utilises a qualitative research design - specifically the use of focus groups which are an effective tool for exploring student expectations and reflections related to their degree program. These groups allow for open and honest discussion among peers, which can help identify common themes and attitudes that may not have been apparent through individual interviews or surveys. By bringing together experiences of students who are at different stages of their degree program, this study can provide valuable insights into the evolution of expectations and experiences over time. Additionally, the group dynamic can promote the exchange of ideas and the development of new perspectives, which can be useful in informing program improvements and initiatives. Overall, focus groups can provide a rich and nuanced understanding of student expectations and experiences, making them a valuable tool for academic researchers and program administrators alike.

Respondents

46 Psychology students were recruited using opportunity sampling from a large Russell Group university in the Northwest of England via posters, course announcements, and word-of-mouth. The interviews took place at two points in 2018 – one at the end of the 2017/2018 academic year, and the other at the start of the 2018/2019 academic year. Upon completion of their degree, fourteen students were interviewed from late May to early June. Additionally, within the second and third weeks of their degree (early/mid-October), thirty two first-year students were given the opportunity to participate in the interviews in exchange for a small amount of course credit. The generalisability of the sample matched the general demographic profile of the University's student Psychology population in terms of sex, age, disability, ethnicity, and academic performance. One student from the first-year group dropped out at the end of the first semester, whilst the remaining students graduated with an array of classifications, averaging a 2:1 classification.

Interview

Nine focus group sessions were run with each containing four to six students. For health reasons a single third-year student was interviewed alone. This interview and one focus group was conducted by the author, whilst the remaining sessions were led by a master's student (a close-in-age peer interviewer) in order to facilitate student comfort in participation and disclosure (Platt, 1981; Devotta et al., 2016).

Focus groups were chosen for a myriad of reasons. Such interviewing style facilitates group interactions stimulating conversation between participants and encourages respondents to

share their own experiences due to the presence and disclosure of others (Kitzinger, 1994). As such, valuable insights into how students perceive their experience of certain areas of study, which can increase their motivation overall, such as the use of low-stakes testing (i.e., testing which did not contribute to final degree scores) can be obtained.

The interviews were semi-structured in order to allow for specific areas of interest to be explored whilst giving participants the flexibility and spontaneity to take the discussion in unexpected directions. Such an approach enables participants to generate and express their opinions and highlights their priority areas within their own vocabulary (Kitzinger & Farquhar, 1999). The group setting also enables students to explore shared experiences (Morgan, 1996), allowing for a more in-depth exploration of the research questions and the generation of rich data. The interviews lasted between 20 and 65 minutes with some groups being more talkative than others. The interviews were audio recorded using voice recorders. Followingly, the recording was transcribed verbatim, without student hesitations or vocal disfluencies (i.e., speech fillers, such as umm or err).

The study took an inductive and realist approach. Despite some areas of investigation being theoretically driven (e.g., the utility of particular A-levels for undergraduate study), the focus groups were conducted in an informal and open manner allowing for the generation of new topic areas to evolve throughout the interviews. By following a realist paradigm, we were able to directly hear from the students about their experiences and perspectives, as opposed to attempting to fit their narratives into a preconceived pedagogical theory.

Analysis Procedure

Thematic analysis was used to analyse the interview data, following Braun and Clark's (2006; 2012) framework. Firstly, the research team familiarised themselves with the scripts and thematically coded the interviews using a realist and inductive approach (e.g., reading the data "bottom-up" and taking participant experiences more or less at face value). Initial themes were then refined using a more theoretically based orientation that focused on identifying key areas of resonance between participant narrative constructions and the theoretical framework. Essentially, the study sought to explore student experience at various levels - superficially (i.e., the surface level within the interview) as well as at a deeper level highlighting themes across focus groups. Following this initial analysis by the author, the data was independently coded and analysed by a fellow researcher who identified similar themes to the author. The data was then revisited to form a final set of five themes.

Results and Discussion

The five finalised themes identified were prior experience, adjustment to university, staff relationships, the experience of studying, and future plans. Together these themes identify some of the barriers and facilitators students face within their transition to higher education (see Appendix 4).

Prior Experience

A common statement across the first-year students was how they envisaged having an A-level in Psychology to be advantageous in their transition to higher education due to having a baseline of prior knowledge already established. This view was based on their experience of the introductory lectures where theories, studies, and researcher names were recognised giving them some familiarity and connection between their secondary and tertiary knowledge. A few students spoke of this as being repetitive but, mostly it was seen as an advantage. Having prior experience can be important for undergraduate students in a number of ways. Firstly, building on existing knowledge enables students to make connections and understand new information more easily and readily (Witherby & Carpenter, 2022). This in turn enhances student motivation as they can see the relevance of what they are learning, ultimately improving content retention (Martin et al., 2017), as the connection/relatability between new information and existing knowledge can be made.

Prior qualifications were seen as valuable for preparing students as exemplified by: *"A-Levels definitely help with coming into university when you've already had that kind of foundation of the tough exams at the end and you have to kind of manage your time studying." (Y1* Interview 1). An apparent difference between the years of study regarding the utility of specific subject prior knowledge was seen. Third-year students viewed an A-Level qualification in Biology to be most beneficial in aiding the study of their degree: "*…the only thing that helped from A-level was doing Biology, I don't think Psychology helped at all whereas Biology gave you more of a head start with like neuro-sciencey stuff"* (Y3 interview 3).

Conversely first year students placed a greater emphasis on the benefits of a holding a Psychology A-Level qualification as they felt this gave them a greater grounding in the information they were currently being presented with:

*"Doing psychology has made me, at A-level really helped me just give it like the background knowledge. It's just like a basic, like foundation but it just helps you out so much like learning it, I can't imagine like having to learn it all from scratch at University [laughs]" (*Y1 interview 2).

Given that the first-year student interviews took place within the first couple of weeks of their first semester, it is possible that these students were unaware of the biological elements entailed in later semesters of their degree, thus focused more on the utility of a Psychology A-level qualification since it is the primary teaching area within these introductory weeks. Research by Hands and Limniou (2023) demonstrates that attaining an A-level Chemistry and/or Biology qualification plays a greater role in first-year success than holding an A-level in Psychology. This finding suggests that it may be worth making a science qualifications a prerequisite for undergraduate entry – an idea also reflected by a year three student:

"There should be a bit of a sort of a disclaimer saying you know `some of the modules are quite heavily science based, like you don't require the science but it may work in your favour to have it`, maybe 'cos then at least people are aware" (Y3 interview 1).

However, it should be noted that prior experience can also have negative effects due to informing student expectations prior to studying which can lead to disappointment, confusion, and/or frustration (Boujaoude, 1992), as demonstrated by one student who

commented: "*I thought we might get like some more applied psychology stuff as in like the theories as well as like what a psychologist does and like, how to be one. Whereas it's more just – this is what psychology thinks*" (Y3 interview 1).

As well as holding direct knowledge, prior discipline experience can help students develop key skills and transferable knowledge to other domains such as critical thinking, problem-solving, and communication skills (Pellegrino & Hilton, 2012). Students also stressed the importance of scientific literacy in helping the development of one's transferable skills and adjustment to higher education:

"I think it's more what you've learnt as well like in A-levels 'cos you learn like how to revise and how to manage your time compared to before then 'cos you have a bit more free time so I think that's probably more useful" (Y3 interview 3).

"*Just like the essay-writing and the problem-solving skills … you came to Uni with them. So, like you came like more equipped going through like things like problems and stuff like on the course*" (Y3 interview 2).

Adjustment to University

Starting university marks a transition period for many students as they move away from home and learn to take care of themselves. Additionally, students must navigate an array of new social situations and emotional states such as building social networks, living independently (Ding, 2017), assimilating to university life/culture, and managing the academic demands placed on them. The transition from secondary to tertiary education is typically marked by a decrease in structured weekly class time, reduced direct contact with teachers, and a greater reliance on self-regulated learning (Richardson et al., 2012; Broadbent, 2017). Across the sessions, students elaboratively spoke about adjusting and adapting to university life. The stories told were more complex than simply talking about what University was like compared to their expectations. Reflection was instead given on the ways in which student study habits changed, how new technological systems were navigated, and even how students moderated their expectations to meet the realities of higher education. Lecturers' teaching style and the classroom environment were frequently mentioned in the upscaling of class sizes from small A-level cohorts to large-scale lecture halls containing hundreds of students.

Many students enter higher education with unrealistic expectations and/or understanding or appreciation of study expectations and demands. This can partially be explained by the difference in pedagogical approaches between educational levels (Cook & Leckey, 1999). Such shifts in approaches, expectations, and complexities can lead to students feeling overwhelmed: "*I was expecting it to be a big jump between A-Level and degree level, obviously it's a lot more work, but it's a lot"* (Y1 interview 4). McInnis, James, and Hartley (2000) discovered that after one semester, students realised that there was a significantly higher workload and time demand for studying than originally anticipated prior to starting. Even in their first couple of weeks, some interviewees noted their struggles: "*I feel overwhelmed. I feel like it's more difficult than I expected it to be, so I don't know so far*" (Y1 interview 3).

This finding suggests that for some students the onset of university culture shock (as labelled by Risquez et al., 2008), is perhaps occurring even sooner than originally thought by researchers. Throughout the interviews, it was obvious that the initial novelty of being at University was wearing off and the realisation of University procedures and customs, particularly regarding the classroom environment, was proving difficult for many students. Such realisations in turn increase student susceptibility to dropping out (Karimi-Haghighi et al., 2022). The sheer size of lectures was a big adjustment for most students, with many feeling a lack of assimilation or immersion in both the lecture halls and the Curriculum itself:

"Look, I mean you can't 'cos there's such a big year group I don't know my lecturers, like I know my supervisor and my tutor but I don't think, I could probably walk past any of them and they'd have no idea who I was" (Y3 interview 1).

Additionally, other barriers were noted such as irritations from typing noises, lack of confidence in-class participation, lecture pace and length, as demonstrated by the following two excerpts:

"*Seminars to me were daunting let alone lectures because I came from a Sixth Form where my biggest class had like seven people in it so then having suddenly having thirty people, I was like whoa this is a lot of people so I feel like I can't speak up so then, never mind the lecture where there's four hundred of us sat in the same room*" (Y1 Interview 5).

"*…they were like very fast paced, like I was just sat there, and I couldn't keep up with all the content and them speaking so fast and it was just a bit overwhelming I think."* … "*didn't realise that lectures would be two hours long, ... after about half an hour my teacher had to give me a break …so being sat down for like two hours straight, after like the first half an hour, I lose focus"* (Y1 interview 5).

Overall, while students acknowledged the differences between University and their previous education, our analysis suggests they did not fully understand the implications of these differences, or the need to adjust their behaviour as a result – a finding also noted by other scholars (see Williamson et al., 2011). University lecturers may need to adjust their content and come up with strategies to address and manage students' unrealistic expectations in order to help them acclimatise to their new learning environment (see Crisp for suggestions on teacher student dialogue).

Staff connections

Inherently the move from secondary to tertiary education involves changes in teaching styles, expectations, support, and contact with lecturers and other faculty members. Unsurprisingly students' perceptions and their working relationships with staff members, emerged as a key theme. As the literature notes, University students value academic staff who have a positive attitude, a friendly demeanour, effective timely communication, and perhaps most importantly enthusiasm in their teaching (Voss et al., 2007; Pithers & Holand, 2006). Enthusiasm was noted by many of the interviewees through the passion staff displayed when teaching about their own personal research areas. Such enthusiasm in lecturers clearly

increased student motivation and carried over to their independent and wider study experiences, as exemplified in the following quotes:

"They've got such a fountain of knowledge from them that it's just so good that you've got that as an on-going resource, they're in the building somewhere, you can go find them, they will help you, most of them will be completely happy to help you and just sit down and listen to your questions" (Y3 Interview 3).

"Brain and Cognition is my favourite, just 'cos err, I was already interested in it, but the enthusiasm of the lecturer, or he wasn't like fully enthusiastic but his, you could tell he really enjoyed it so it sort of rubbed off on me" (Y1 interview 1).

Additionally, lecturer enthusiasm was also noted by the interviewees through lecturer idiosyncrasies and performance style:

"I find that some of the lecturers are quite engaging though as well, like you can kind of, they'll put in some of their own quirky jokes and stuff which I quite like cos I was quite worried that it was going to be like really mundane lectures sort of really kind of tight lecturers but actually they're a lot more engaging and you can tell that they're really passionate about their subject field as well" (Y1 interview 4).

Short and Martin (2011) found that students performed significantly better when lectures were given in a performance style - incorporating personal anecdotes and audience interaction – over when a presentation style focusing on information transmission with no interaction. Overall, students reported good relations with the academic staff however many noted such rapport grew over time with class size being a significant barrier to developing these relations specifically within their first year of study:

"I think definitely one of the things we miss out on being such a massive course is having like that closer relationship with members of staff. You know when you've come from school and in A-levels you're in like classes of 15 and you have really close relationships with your teachers. … So, I think that's definitely one of the things I've found most helpful but it is one of the things that you miss out on in the course because it so massive" (Y3 interview 3).

"From the initial [meeting with your supervisor] *that makes you like not just a face in the crowd. Like, if you did that in first years like you'd know your lecturers. Like, only meeting them in this year and stuff is like great but it's one of them things where you wish you'd have known them since first year 'cos they'd have been of such help*" (Y3 interview 2).

The Experience of Studying

Within this theme, three main subsections emerged – changes in study habits, time management, and technology use. Within the study habits subtheme, there were distinct differences between year groups regarding study habits and methods. Many first-year students predicted that they would need to change their study and revision habits to adapt to the new learning higher education environment – a finding also seen elsewhere in the

literature (see Pownall et al., 2021). Finding their appropriate method/study technique drastically varied across these students with many still trailing different methods:

"I still haven't found something that's worked for me, like I didn't find it in A-Level and I'm still trying out different methods for me. I think the only one that came close to slightly working was having visuals so like something colourful to look at" (Y1 interview 5).

For third-year students, many reflected on how they had to adapt, adjust, and try different methods until they reached a system which worked:

"It took me ages to try and work out the best way to actually take notes just in lectures and stuff, like I just spent like so long not, like just trying to figure out the most like efficient way to do it … I was like this is so difficult … kind of made like my own versions" (Y3 interview 1).

Consistent with other scholars (see Hadwin et al., 2001) students spoke of changing their study habits to fit their routine, workload, and specific modules due to differences in the ways they would be assessed, in turn informing their exam approach and revision methods. In particular, third-year students recognized how much more work was required at the end of their degree compared to the start as the following exchange shows:

"Student 1: I don't know what we did with our hours in first year like, what did we do?
Student 2: [inaudible] Just like watching some TV, like being hungover! [laughs]
Student 1: We just wasted so much time.
Student 3: Now it's like there's not enough hours in the day.
Student 1: Yeah, it's just like completely different, isn't it? [laughs]" (Yr3 interview).

Time management is an essential skill required by students, with many noting procrastination and other forms of distraction as two of the biggest barriers to effective time keeping. As one first-year noted:

*"I procrastinate a lot …, it's just sort of trying to motivate yourself to do it quickly, I often start things and then I'm like `I'll come back to that later` and then I leave it really the last minute" (*Y1 interview 1).

As evidenced, many students were aware of their working habits and noted their tendencies to procrastinate with the pressure of an emerging deadline inciting productivity:

"*I made study timetables but I didn't have the self-control to stick to them. I think I tried every method possible, I tried working with somebody, I tried rewarding myself and it just never worked for me, and I think I always kind of procrastinated and I work best under stress, that is when I do all*" (Y1 interview 4).

This response was very common throughout the interviews and is noted across the literature with procrastination tendencies and emerging deadlines forcing students to improvise, prioritize tasks, and find actionable and creative solutions (Grant, 2016; Mohammed, 2021). Distractions were another commonly mentioned barrier to learning with the use of technology (e.g., one's mobile phone, or laptops) and/or living in communal student

residential spaces (of which many had never experienced before), thus requiring students to seek quiet working environments, such as the library:

"It's also getting distracted especially, I think I just need to work in the library because when I work back at the accommodation, like I normally didn't have my phone on me, like at A-Levels I didn't, but now it'll be next to me and someone will be like "Oh do you want to meet up?" or "I'm doing washing, do you want to come down?" And I'll be like, "Oh yeah" and then I'll just leave it and then I eat tea and then I'll just be like "Oh I'll do it all tomorrow" and it's just something that I shouldn't do" (Y1 interview 5).

As well as distractions caused by fellow students and living environment there are the distractions within the classes themselves, for example Limniou et al., (2020) found that device used in lectures while mostly offering a positive addition to learning they could also act as a distractor particularly when there was a mismatch between learning and the device information. Indeed, despite some initial difficulties adjusting to the new software and technologies used in higher education, these sources played an overwhelmingly positive and facilitative role in student experiences. Consistently students talked about helpful technological resources ranging from lecture recordings (aka stream captures) and Blackboard - the University's VLE including some of its features such as virtual discussion boards. The use of recorded lectures (aka stream captures) increased as students progressed through their degree with its main use being to catch up on missed lectures, or recap the lectures themselves at the student's own pace for clarification or revision purposes:

"*It's definitely a useful resource regardless of whether you do make use of it or not because especially if, erm it might not necessarily be because you haven't understood the lecture and you feel like going over it again, if you are like ill, or for whatever reason you cannot make it*" (Y1 interview 1).

Stream captures also played an important facilitating role for those with a learning difficulty or disability, and for international students who may not be studying in their first language (Panopto, 2018), as the following two excerpts show:

"[I have a] hearing impairment and things like that so from an accessibility point of view, I feel it is quite essential at times to have it even if the majority of people don't necessarily use it" (Y1 interview 4).

"Because I'm the only one listening to it, I can pause it when I need to, like I can slow it down to my pace to make the notes when I want, like if I've heard a certain part, I'll pause it, make notes on it, replay that part to make sure I've got everything then move onto the next part." (y1 interview 5).

As well as longitudinal increases, periodic increases in the use of stream captures were also noted, with heightened use occurring during exam periods for both first and third-year students. The convenience of having learning resources online was also appreciated by students to accommodate their routine, work patterns, and availability:

" [The VLE] makes it really easy to do work at whatever time you have, so erm, like there was a certain bit of reading that we had to do that was available on Blackboard so it was really easy when you have a spare hour to like make the most of that and you can be in your room doing that as opposed to having to go to the library, find the book, find the right bit" (Y1 interview 1).

The convenience of VLE's discussion board feature to interact with both the lecturers and fellow peers was also noted:

"Although not all lecturers replied efficiently, I thought it was really useful 'cos obviously everything was all in one place … the discussion boards were good," (Y3 interview 1) … "there's some things you wouldn't have thought of and then someone's asked a question on it and you get the answer and you're like "oh!" [laughs]" (Y3 interview 2).

One aspect that varied across modules and affected student posting on discussion boards was the ability to do so anonymously: *"Yeah. Like there's been times that I've done it and not realising it's not anonymous, so my name was coming up and I was like "god, I sound so stupid"* (Y3 interview 2). Students reported greater use in this feature when their responses were anonymous. This preference is likely to be driven by anxieties over social desirability and being wrong in front of both their peers and lecturers (Freeman & Bamford, 2004).

Future Plans

Prior experience to entering higher education and then throughout can help students identify and explore their career interests, as well as help them develop desirable skills and knowledge in the eyes of employers. First-year students displayed an array of perspectives with some starting their degree with clear career aspirations whilst others had no idea and were open to seeing where their interests fell, as noted in the following two quotes:

"I think I want to… but my main goal is to become a clinical psychologist, but we don't have that module until next year" (Y1 interview 3). "*… I think it's definitely open yeah, I'm not completely set in what I want to do yet, I'm not completely sure ... over the next three years that I'll get different tastes of different parts of Psychology and feel that maybe I might find something completely new that I might be more interested in … so I've got three years to decide" (Y1 interview 4).*

Conversely, many of the third-year students reported that during their degree they had learnt about numerous career options that they were previously unaware of and for many their career aspirations had changed. Whilst the scope of modules and training in different Psychology subfields widened as the course progressed, many students wanted these course/disciplines to appear earlier on in their course. The main drive for this was to manage student expectations and provide an accurate depiction of subfield content and possible career pathways within it. For example, one third-year student noted:

"I just had so many misconceptions of what it actually entailed, and I think people think like it's forensic psychology like massively glamorised and I actually don't, don't really know what

it is until you, and I think what people think they want to do is like clinical psychology in a forensic setting rather than actual forensic psychology" (Y3 Interview 3).

Future careers/directions also varied across the third-year students with some wanting to leave academia, others wanting to take a break before returning for post graduate study, whilst others planned to immediately pursue this avenue in a variety of related subfields of Psychology including forensic and clinical, it's likely that students were focused on these areas as they are the areas in which university offers as masters degrees and doctorates.

Conclusion

Taken together these results offer an insight into how students' prior experience and transferable skills support their adjustment to university life. Several factors blocking the efficacy of first-year student adjustment were large lecture sizes and their fast pace, and the reduction in familiarity and working relationships with the lecturers. The passion of staff members for their research topics was noted to spark student interest and motivation, which is carried through in their experiences of studying, exam preparation, and even future plans. By the time students came to graduate they looked back on their period of adjustment and wondered why they found it as stressful as they did. As a result it may be worth encouraging students who have graduated to speak to students who are just starting to provide reassurance that this feeling of disequilibrium will pass as they successfully navigate the transition to university.

As with any research, the study had a few limitations. By focusing on the academic side of the students' experiences, the narrative presented overlooks many of the other multiple and concurrent transitions the students experienced when starting their degree, such as navigating new friendships and living independently – often for the first time. By focusing solely on academic experiences and excluding the consideration of students' social and extracurricular activities, the study's validity is lowered since these areas have a dramatic effect on a student's academic career (Guilmette et al., 2019; King et al., 2020). For example, a lack of balance between academic and non-academic responsibilities in either direction can negatively affect a student's University experience. A future study could explore this area as well as the academic expectations of students. Since these interviews were conducted there have been considerable changes throughout the education system, both in a pedagogical and departmental sense as a result of the global COVID-19 pandemic. As such, current students may face additional challenges (or facilitators) that were not a part of this study's student experiences such as online examinations, increased use of novel technologies, and a greater emphasis on mental health and student well-being. (Liverpool et al., 2023; Copeland et al., 2021; Lischer et al., 2022). Therefore, this data may not accurately and fully reflect the current student experience. As students transition in (and back out of university) they will face both barriers and facilitators within their experience, however hopefully overall it will be a positive one, as reflected by the advice given by a student: *"Be yourself, don't be worried and enjoy every single piece of university. It is a good experience, and you should love it"* (Y1 interview 6).

8. Discussion

The five studies presented in this research project examine how various factors such as prior knowledge, motivation, learning environment, learning approaches, and metacognition can impact academic success. These, in turn, can positively affect employment outcomes, earnings, and future career prospects for students in the UK. Indeed, a study by the Office for National Statistics reported that workers with higher levels of education and qualifications tend to have higher median hourly earnings (up to £10,000 higher) than those with no qualifications (ONS, 2021). By examining the factors that influence student learning and academic performance, it is possible to gain valuable insights into how educators and policymakers can enhance the learning environment to better support student success in traditional universities. This thesis draws on the factors suggested by Biggs's (1993) Presage-Process-Product (3P) model of teaching and aims to explore the complex interplay between various student factors, teaching context, learning approaches, and learning outcomes in depth. Through this exploration, this PhD seeks to provide practical recommendations for improving learning environments and promoting student success in higher education. Each of these studies will now be discussed in turn, followed by a discussion with suggested amendments to the 3P model in light of the PhD findings.

8.1. Study One

This research project looked at one of the key presage factors involved in student characteristics and examined the role of prior knowledge in students' academic performance. This study specifically considered whether prior learning in scientific topics adequately prepared students to succeed in their first-year modules. Findings Indicated that the usefulness of previous knowledge for students in Biology and Statistics courses depended on the specific subject matter. Specifically, within the Psychobiology module the usefulness of having an A-Level Psychology qualification was found to be less significant than a Chemistry or Biology A-Level qualification. This suggests that Psychology qualifications might not be as advantageous as the other two scientific disciplines analysed when it comes to mastering the Psychobiology module. Vocational qualifications were shown to be less helpful than academic qualifications in terms of benefits. In the analysis, a BTEC was shown to have an overall negative effect on grades, with students holding this qualification being more likely to be working at the lower end of the grade spectrum. While vocational qualifications can be valuable for developing practical skills and knowledge in specific industries, the research highlights potential limitations of these qualifications when it comes to promoting academic success and achieving higher grades. This is also apparent for first-year undergraduate Psychology learning outcomes, where effects were limited. This finding could be explained by the nature of the qualification. Vocational qualifications are designed to provide practical skills and knowledge for specific job roles or industries, whereas academic qualifications are geared towards theoretical knowledge and critical thinking skills. The study could have implications for students who are considering which subjects to study at school or University, as well as for educators and policymakers involved in curriculum development. It highlights the importance of considering the interrelationships between different subjects and modules, and the potential impact of certain qualifications on academic performance. By understanding these relationships, educators and policymakers can better support students in their academic

pursuits and promote a more well-rounded educational experience Overall, University studies are focused on assisting students to develop critical thinking, analytical and research skills, and the students with vocational qualification background would have had less focus on these skillsets. Therefore, vocational qualifications may be less useful in an academic environment as they may not provide the same level of preparation to first-year students for their academic work.

Lastly, the study showed that the number of science qualifications was not cumulative in terms of their effect on grades suggesting that the key part of students' prior knowledge was the development of scientific and Psychological literacy which enabled them to understand key Psychologically related topics such as the function of a neuron. This "literacy" in terms of learning and understanding the material is a theme that recurred through all the other studies and is a key area for further study. Students who have developed good literacy skills in their chosen field tend to find the transition to University less demanding than those who need to learn these skills alongside the first-year demand. Indeed Harris et al., (2021) noted that while students in the UK found value in their Psychological literacy, (such as the understanding subject-specific knowledge, and developing critical thinking), they did not always recognise their previous background in this area as fundamental knowledge and skills needed for academic success. This is perhaps because they might exhibit good levels of metacognition and self-regulation. This finding is in line with Zuffiiano et al., (2013) who highlighted that prior successful performance which combines effort and ability attribution is a stable predictor of future performance. Therefore, more successful students are also likely to display independence in learning (Gagne & St Pere, 2001) even if their studies were disrupted.

8.2. Study Two

Study two examined student approaches to a task (process) and how this was impacted when the teaching context changed (presage), alongside also examining how student characteristics of preferred ways of learning (presage) affected learning outcomes. Specifically this study explored students' use of their VLE both during a normal teaching academic year (2016-2017) and during periods of disruption caused by industrial strikes (across a few weeks of the second semester of the 2017-2018 academic year). The findings of this study were mixed but one, perhaps unsurprising, result was that highly successful students did not change their behaviour. It is suggested this result could be due to these students already possessing high levels of independent study skills. Equally, the poor-performing students appeared to lack the self-regulation skills needed to engage with the course material. Additionally, when the immediacy of lectures and coursework was removed, these students were disengaged with the material and reduced the time spent studying across the semester. Increased their efforts and study time only increased immediately before the examination. The biggest changes in learning behaviour were observed by students in the middle range of grades (2:2 and 2:1). These students moderated their behaviour by slightly increasing their access to the VLE, but this was mostly clustered at a time point towards the end of the strike. This finding was perhaps mediated by the effects of the low stakes testing which took place every two weeks with one also due towards the end of the strike period. As a result, it would be interesting to explore whether these students would have behaved in a different way had their coursework been purely cumulative. This study may have implications for other periods of disruption such as the recent COVID-19 pandemic suggesting that for some students it may be more beneficial

to have features within a VLE that encourage spaced practice (i.e., regular study sessions) rather than the massed practice which typically occurs a day or two before the examinations take place.

Student learning behaviour during periods of disruption has been strongly linked to levels of self-regulation as mentioned in a recent study by Limniou et al., (2021), using a subscale from the DSML measure. Results found that students with high self-regulation skills were more likely to adapt to online learning compared to those who presented lower levels of self-regulation. These specific students tended to instead show a preference for regularly scheduled face-to-face teaching in a clearly structured curriculum. This study highlights the need for utilising potentially different approaches (i.e., learning settings and curriculum structure) for different student clusters of students, based on their self-regulation skills (Rotgans & Schmidt, 2009). When considering the findings of this study, it should be noted that when compared to less regulated, highly self-regulated learners likely were demonstrating a greater control over their learning process so were more aware of their own learning needs and strategies. One explanation for this is that these students were able to use better metacognitive strategies to reflect on their learning progress and adjust their strategies accordingly. Moreover, they are also likely to be more motivated to engage in deep learning by actively engaging with the material and making connections between different concepts. However, these strategies may have varied over time, and it is important to consider how these fluctuations may affect student outcomes - a concept that was explored in study three.

8.3. Study Three

The purpose of the third study was to examine how Psychology students' approaches to learning and metacognition change over time. This study is mostly focused on the process elements of Bigg's (1993) model, although it briefly considers how the assessment type (presage, teaching context) affects behaviour and explores this changes over time. The results showed that while students' ability to regulate their own metacognition increased, their actual metacognitive knowledge did not. This finding aligns with previous literature such as that of Young and Fry (2008) and suggests that by the time students were accepted into university their metacognitive knowledge has been already well developed based on their previous learning. Study three also found that both students' surface and deep approaches to learning showed changes over time, with the former exhibiting distinct changes from the baseline to the second semester of year 1, and the latter decreasing over time. Interestingly, the changes in students' learning approaches and metacognition did not have a strong association with their final grades, implying that other factors might be impacting their academic performance, such as the difficulty level of the course material or external factors such as the time spent studying. This finding is also echoed by Baeten et al., (2010) who found that while students' deep learning approaches often resulted in qualitatively better learning outcomes, the use of deep approaches was not always reflected in higher quantitative learning outcomes. Outcomes such as test scores or grades often measure more superficial knowledge, such as the ability to recall information or solve problems using rote memorization or formulaic approaches. Therefore, outcomes based solely on exam and coursework results may not necessarily reflect the level of understanding or students' ability to apply material that is learned through a deep approach. Overall, the findings from this study suggested a complex relationship between student learning approaches and academic performance. As the

workload increases and assessments become more challenging, students tended to adopt more surface learning approaches. Therefore, it would be essential to encourage the development of metacognitive regulation abilities among students by helping them manage their learning effectively and improve their academic performance. Metacognitive regulation is an important component of self-regulated learning and is often assessed using instruments such as the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich et al., 1991).

8.4. Study Four

This study sought to explore a range of presage and process factors, and test how well these factors enabled the prediction of student performance. The MSLQ measure is a frequently used in education, however, it has been criticised for several issues such as length, ideal point items, and poor discriminative values. Therefore, the fourth study aimed to develop a new shorter and more focused measure that addressed similar motivational concepts in student learning. By developing this measure from the ground up using input from both students and teachers, the Diversity Strategies for Motivation in Learning (DSML) blended student motivation with their engagement under the directions of cognition, behaviour, and affection. Some areas in the initial MSLQ questionnaire, such as the learning approach and metacognitive items, did not appreciably add to the validity and were discarded. Following exploratory and confirmatory factor analysis, the diversity of strategies for motivation in learning (DSML) was developed containing 26 items, including six new factors (course utility, self-efficacy, test anxiety, self-regulation, study strategies, and source diversity). Together these six factors accounted for 23% of grade variance, although interestingly test anxiety did not predict grade. These findings align with Theobald et al.,'s (2023) who suggest that test anxiety, while distressing for students, is not directly related to grade. The DSML has successfully been tested with university students in Saudi Arabia (Alsharif & Limniou, 2020) and revalidated with further students from different disciplines at the University of Liverpool. Some of the subscales have also been tested independently presenting good reliability and validity for use in separate questionnaires (Limniou et al., 2021; Olojugba & Hands, 2023). The DSML could be also used as an early alert tool for students who are at risk of not completing their studies. The DSML has been used in conjunction with focus groups to gain a deeper understanding of students' learning strategies and experiences, which were qualitatively explored in study five.

8.5. Study Five

The final study in the thesis also explored a range of presage and process aspects through a qualitative lens. The fifth study utilised semi-structured focus groups to explore all of the factors which affect student learning and experience, focusing not only on what affected student learning but adding a temporal dimension to consider how this may have fluctuated across time. First-year students who had only just transitioned to university and tried to adapt themselves to the new environment were interviewed in focus groups, as well groups with third-year students who had completed their degree (although awaiting their final graduation marks).

The findings of this study complement the prior four studies. In particular, it has been found that in relation to prior knowledge students initially valued Psychology as the most helpful qualification feeling that this had prepared them for the course. Conversely, by the time students were ready to graduate, they no longer felt that their Psychology qualification was particularly helpful and instead placed emphasis on Biology as being the most. This finding is echoed in study one for which a quantitative analysis was followed including the entry admission criteria and students' grades. When discussing VLEs and other learning technologies both groups of students recognised them as tools to aid their learning. Although when interviewees entered their university studies many found these tools difficult to grasp, however once they had, the majority of students acknowledged these tools as helpful for their learning. Interestingly in one interview, a student highlighted an issue that could help explain some of the findings in study two. They pointed out that it was possible to download all the information used throughout the semester right at the very start of it. Thus, some students were simply engaging with the material they had initially downloaded having no need to access the VLE until tests were administered. This learning habit might alert researchers regarding the learning analytics data that are used from the VLE systems. While metacognition and learning approaches were not directly discussed as factors affecting students in the focus groups, there were several comments that linked the study approach to self-regulated learning habits, which underpin metacognitive learning approaches. Students' exploration of their own readiness to change is an important component in programs designed to develop self-regulation (Jakubowski et al., 2004). Students also discussed some of the other elements measured by the DSML tools such as test anxiety, course utility, and future aspirations such as a wishing to train as a clinical psychologist.

Examining the overall themes highlighted in the introduction, this PhD contributes to the field of study in four main areas 1) transition and experiences in higher education, 2) understanding prior knowledge and learning approaches, 3) exploring the role of digital learning tools, and the 4) overall factors affecting student outcomes and performance.

Through examining transition and early experiences in Higher Education the studies presented highlight the importance of considering students' prior knowledge and qualifications when examining higher education transitions and help develop an understanding of how this may impact current and future performance. Different subject backgrounds and types of qualifications can have varying impacts on academic performance so entry tariffs should be adjusted to ensure those undertaking the course are properly prepared to do so. Importantly, vocational qualifications may have limitations in promoting academic success in traditional university settings, as they may not provide the same level of preparation for academic work. As a result, students entering with such qualifications should be given more support to develop their academic skills particularly in academic writing. Understanding the difficulties in early transition can help in developing interventions and expectation management in the early weeks of study. Equally through understanding the issues that students arrive with can help educators design their courses to support students more effectively based on their prior knowledge and the impact this has on their learning approaches.

Students' prior knowledge, specifically in their chosen field of study, plays a crucial role in their academic success. The development of scientific and psychological literacy is particularly important in understanding key topics. Students who have developed good literacy skills in

their field tend to have an easier transition to university. Moreover, students who exhibit good levels of metacognition and self-regulation are more likely to succeed academically. However, it must be acknowledged that their early experiences particularly with assessment will lead to students moderating their approaches based on early university experiences. As the studies above show such experiences tend to play a pivotal role in how students approach their learning as well as the tools they choose to use in their studies.

This PhD also sought to explore the role of digital learning tools on their learning performance. Digital learning tools, such as VLEs can have both positive and negative impacts on student learning behaviour. Highly successful students tend to have pre-existing independent study skills and do not change their behaviour significantly when using VLEs. However, students with lower self-regulation skills may struggle to engage with course material, especially when the immediacy learning seems removed. The design of digital tools should consider including educational theory in their design such as promoting spaced practice and regular study sessions to support student learning. The findings highlight the importance of considering students' prior knowledge, learning approaches, metacognition, and self-regulation when designing effective learning environments.

Multiple factors influence student outcomes and performance in higher education. These factors include prior knowledge, learning approaches, metacognition, self-regulation, and motivation as well as non-academic factors. While deep learning approaches are often associated with better learning outcomes, exam and coursework results may not fully reflect students' understanding and application of material learned through deep approaches. The development of metacognitive regulation abilities and effective learning strategies is essential for improving academic performance. The development of practical recommendations based on these factors can enhance the learning experience and support student success and the examination of these factors provides valuable insights into the complex interplay between student factors, teaching context, learning approaches, and learning outcomes.

Overall, the findings of the studies on student outcomes align well with Bigg’s (1993) 3P model, emphasising the importance of considering the needs of learners, using effective instructional strategies, and measuring learning outcomes in a variety of ways. This conceptualization of Biggs' (1993) model is based on a combination of previous research in the field and the findings of the researcher's own PhD study. The studies all drew from existing literature and research on student approaches to learning, considering how these then impacted their academic performance to develop a deeper understanding of Biggs' (1993) model. Additionally, the researcher's own PhD findings provided further insights and perspectives regarding the model thus allowing for its refinement and expansion of the original framework. In other words, the researcher synthesized previous research and their own empirical data to develop a more nuanced and comprehensive understanding of Biggs' (1993) model.

8.6. Overarching Theoretical Implications

The 3P model, developed by Biggs (1993) has been used to evaluate teaching and learning environments and assess the factors that may influence student learning outcomes. However,

it is important to recognise that the presage and process elements within the model may limit a comprehensive understanding of the complex feedback loops that affect students (Carless, 2019). This is partially acknowledged in Entwistle and colleagues' (2002) model which recognises the interactive and reciprocal nature of each of the facets, yet still however lacks the temporal element that impacts future behaviour. Ultimately, all these elements play an interactive and reciprocal part in how students develop and maintain motivation and engagement with their learning, regardless of whether they are confronted with a similar or novel task (Brophy, 2013).

The 3P model is a descriptive framework that organises the elements of a specific system, logically within a linear process. For example, the model suggests that student characteristics affect their approaches to task processing, which in turn affects their learning outcomes. However, student learning occurs within a teaching context that influences both the nature of learning and its results. Therefore, it is suggested that while the 3P model helps researchers and teachers conceptualise learning areas, more emphasis needs to be placed on the connections between the various presage, process, and product factors. Additionally, acknowledgement is needed regarding the temporal element of student development across their degree, along with the consideration that these processes are often different depending on the level of granularity examined.

Based on these shortcomings and the presented findings in this PhD, it is suggested that the 3P model should not be modelled through a linear or unidirectional process, but rather a cyclical one that involves ongoing feedback loops between the presage, process, and product elements. The presage factors, which include student characteristics and the learning environment, influence the process factors, such as teaching practices and instructional strategies, which in turn, affect the product factors, such as learning outcomes and achievement. However, the product factors can also feed back into the presage and process factors, creating a continuous cycle of learning and improvement (although, the cycle can fail for disengaged and drop out students). Therefore, it is important to consider the temporal element and the dynamic nature of these feedback loops when using the 3P model to evaluate teaching environments and support student learning.

This conceptual loop affects student outcomes across the three stages, with each influencing the next making outcomes arise both directly and indirectly from each stage. In addition to this loop being affected temporarily, researchers should consider the level of measurement of the task of interest – due to contextual differences such as where and what level the task is administered in, as well as its perceived value by students. Researchers should also be aware of task temporal effects on each of the factors which can strengthen or weaken the effects of the loop affecting learning outcomes. As such, a multileveled model is necessary to fully capture the complexities of the factors affecting student outcomes, as shown in Figure 15 below.

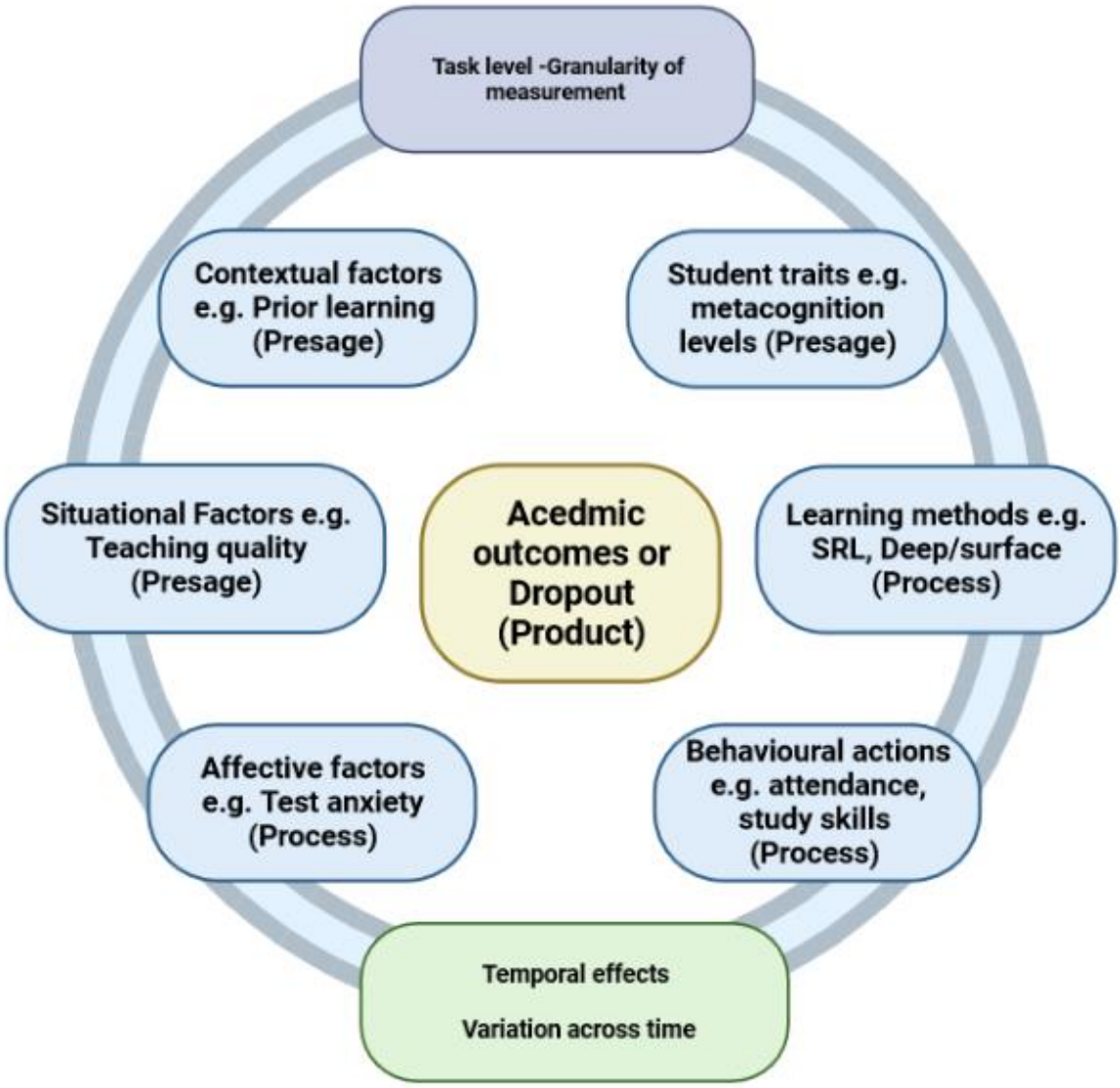
While the 3P2T model helps to further conceptualise student factors that impact their outcomes, it still only just starts to address the complexity of factors affecting students learning. One way of beginning to address such complexities is by providing personalised learning.

Personalized learning refers to an educational approach that seeks to tailor instruction and learning experiences to the specific needs, interests, and abilities of individual students. This

approach recognizes that each student has unique learning styles, preferences, and needs, and it aims to provide learning experiences that are relevant, engaging, and effective for everyone. In personalized learning, students are given greater autonomy and control over their learning, and they are often encouraged to take an active role in this process. Teachers and instructors may use a variety of tools and techniques to personalize instruction, such as adaptive learning software, data analytics, and one-on-one mentoring or coaching.

Figure 16

Proposed 3P2T Model



The goal of personalized learning is to help students achieve their full potential by providing them with the support and resources they need to succeed. By customizing learning experiences to meet the unique needs of each student, personalized learning can help to improve student engagement, motivation, and achievement, as well as foster an enduring love for learning. The growing expansion of technological innovation and learning software offers the possibility for personalised learning to become more accessible to users, however

widespread adaptation and adoption by universities tend to be slow and require a high level of organisational changes. When evaluating student achievements, it is crucial to consider how the organizational approach can impact the factors that influence the learning process. In particular, it is important to address the disparity between systems thinking and non-systems thinking.

A systems thinking approach to education would recognize the importance of addressing these academic factors at the individual level, such as providing differentiated instruction to students with different levels of prior knowledge or implementing interventions to improve motivation for students who may be struggling. On the other hand, a non-system thinking approach may ignore or downplay the impact of these academic factors and instead focus solely on external factors such as funding or teacher quality. This is particularly evident in the difference between additive or deficit models vs interactive models of learning and teaching. Deficit models hinging on the requirement of additional items needed to solve learning and teaching issues often oversimplify the complex nature of this issue. These models tend to pinpoint a single factor as the root cause of poor student performance. For instance, if students fail to achieve the desired level of academic success, a deficit model might assign responsibility to a specific person (i.e., the student) or a thing (i.e., lack of effort) as the problem. Subsequently, the solution would then be to address that specific issue, consequently expecting the resumption of student learning.

This approach fails to consider the interactive and dynamic nature of learning within the teaching environment. Conversely, interactive models recognise this complexity of the teaching environment and consider the various factors that contribute to student learning outcomes. The proposed 3P2T model aims to include some of this complexity while acknowledging that learning is influenced by multiple factors, such as the learning environment, teaching practices, student characteristics, and the social context. By using interactive models, teachers can take a more comprehensive teaching approach in assisting students. This approach includes recognising that addressing a single issue may not be sufficient nor result in the changes that are hoped for. Instead, the model suggests that teachers should take a more holistic approach to supporting student success which considers the interactive and dynamic nature of learning and the teaching environment. This approach acknowledges the fact that student success is indeed a multi-faceted web of complex interactions dependent on a variety of factors.

In the introduction three research questions were posed, these were:

1. How has the digital transformation of higher education impacted the relevance and applicability of the Biggs 3P model in understanding factors affecting student outcomes?
2. What are the most important contextual and personal factors that interact with the Biggs 3P model to predict students' academic success in the contemporary educational setting?
3. How can an updated version of the Biggs 3P model, incorporating the influence of digital transformation and diverse learner contexts, provide a more effective framework for supporting student learning in today's rapidly changing education landscape?

The digital transformation of higher education has had a significant impact on the relevance and applicability of the Biggs 3P model in understanding factors affecting student outcomes. The model, which encompasses presage (student characteristics), process (teaching context and learning approaches), and product (learning outcomes), provides a framework for understanding the complex interplay between these factors. However, with the integration of digital technologies in education, new contextual and personal factors have emerged that interact with the 3P model.

In terms of relevance and applicability, the digital transformation has expanded the learning environment beyond the traditional classroom setting. Online learning platforms, virtual learning environments (VLEs), and digital resources have become integral parts of education. These technological advancements have provided new opportunities for personalised and flexible learning experiences, options that in the future technology such as AI will be able to further refine. Students can access educational materials anytime and anywhere, collaborate with peers remotely, and engage in interactive and multimedia-rich learning activities. As a result, the traditional boundaries of time and space have been disrupted, influencing the factors that impact student outcomes. Therefore, the nature of education is currently, and will continue to experience rapid flux and development and by shifting to a non-linear 3P model which takes account of time and task will better enable educators to consider a contribution of contextual and personal factors.

Contextual factors such as the availability and accessibility of digital resources, the design of online courses, and the integration of technology in teaching methods have become important considerations in understanding student outcomes. The effectiveness of digital learning environments, the adaptability of instructional strategies to online settings, and the support provided to students in navigating digital tools can significantly influence their academic success. Thus, it is vital that we continue to address these in the updated model. Consideration also needs to be given to personal factors, including students' digital literacy, self-regulation skills, and ability to adapt to online learning, regarding the crucial role they play. The digital age requires students to possess not only subject-specific knowledge but also digital skills and competencies. Students who are comfortable with technology, possess strong self-regulation skills, and can effectively manage their learning in online environments are more likely to achieve positive outcomes.

An updated version of the Biggs 3P model, incorporating the influence of digital transformation and diverse learner contexts, can provide a more effective framework for supporting student learning in today's rapidly changing education landscape. This updated model would consider the new contextual and personal factors that have emerged due to digital transformation. It would acknowledge the impact of digital resources and learning environments on student outcomes and highlight the importance of developing students' digital literacy and self-regulation skills. Additionally, it would recognize the need for personalized and adaptive approaches to teaching and learning in online settings.

By integrating these updated elements into the Biggs 3P model, educators and policymakers can gain a deeper understanding of the factors that influence student success in higher education. This understanding can inform the design of inclusive and effective learning environments, the development of tailored instructional strategies, and the provision of support mechanisms that address the diverse needs of learners in the digital age. Ultimately,

an updated version of the model can contribute to enhancing student outcomes and promoting their overall success in today's rapidly evolving educational landscape.

To summarise, this thesis has explored many of the facets which affect student learning outcomes, presented an updated measure – the DSML, highlighted the complex web of academic factors affecting learning and consequently built off Bigg's (1993) 3P model to provide a new theoretical contribution to the field – the 3P2T model. In many ways this body of work has only just begun to scratch the surface of an endlessly complex picture of student success (or failure). While these findings shed light on some of the factors affecting student outcomes, it is important to consider the limitations of this research, which could have impacted the generalizability or validity of the results.

8.7. Limitations

In all of the research studies, academic achievement was assessed through the use of grades as a metric. However, this evaluation method did not fully account for variations in the type and degree of learning strategies employed (McCune et al., 2011). By concentrating on the effects of deep vs surface learning, the "strategic approach" that students might follow to match their learning approach to the assessment at hand was overlooked. For example, despite deep learning often being viewed as inherently more beneficial to learning, the assignment format in year one (multiple choice question exams) meant first-year students were better served using a surface approach due to such questions targeting the memorizing of discrete facts rather than demonstrating understanding. Additionally, it should be noted that the surface level learning scale has been shown to be far less sensitive to minor variations in students' behaviour, lowering its statistical reliability (Snelgrove & Slater, 2003). It's also possible that some of the correlations found in the data could partially relate to background factors as well as the variables under consideration (Schellings & Van Hout-Wolters, 2011). In this case, variability in the scores obtained on different occasions does not necessarily cast doubt on the adequacy of the test instrument, however such background factors may help explain the variation in longitudinal findings. Longitudinal studies of this sort are hard to carry out due to the high probability of attrition with participants likely to decline to participate in follow-up sessions or withdraw from their degree program. As such, the final dataset may no longer be representative of the original sample (Richardson, 2004). This variation in findings can also be seen in study one, and it is argued such variations could be due, at least in some part, to the differences in specifications between A-level exam boards. Having said this, part of the variation could also be accounted for by a lack of previous exposure to the particular ways of teaching, expectations, and software used in this institution. Indeed within the studies new technology and getting to grips with this has been an issue for students, for example understanding how to use the statistical software SPSS. As a result of needing to learn this software some students struggled and teachers needed to spend time focusing on teaching the software rather than the course material, a finding that has been echoed in the literature, Mehta and Black (2012; Black & Mehta, 2011) found that university lecturers rated students' level of preparation in data analysis and statistics as the lowest of all the areas of psychology. However, there may be a somewhat simpler explanation. In all the studies presented, and indeed in much of the literature, contrasting results are evidenced and are often attributed to individual differences within various psychological and learning constructs such as metacognition and motivation (Gašević et al., 2016). Conversely, it's also possible that the

impact of individual variations is not consistently observed in the dataset because clusters of dissimilar students may counterbalance the effect of others.

Correlation is frequently employed to investigate connections between variables. However, a simple correlation assumes a linear relationship, whereas practical scenarios may involve curvilinear relationships. Consequently, the utilisation of linear correlation may suggest there to be no relationship where in fact one exists when using a curvilinear model. Additionally, it is crucial to acknowledge that the data may support a model in which the directionality between the variables is opposite or bidirectional (Kember & Leung, 1998). It is also important to note at this point that even the positive findings of these studies should be interpreted with care, as Simpson (2017) points out, statistical significance does not always correspond to educational significance. When a study has a sufficiently large sample size, it can lead to the conclusion that there is a significant difference between two groups, even though from an educational standpoint the differences may be considered trivial. Hence where possible effect sizes have been given across the studies, ranging from small to relatively large, it's important to consider these findings contextually. One way of addressing this would be to triangulate the findings between studies. Unfortunately, only a small number of students completed more than one study; however future studies could consider this approach as a way to strengthen their findings. As Bond and Fox (2007, p.4) point out "…scales to which we routinely ascribe that measurement status in the human sciences are merely presumed … almost never tested empirically". The use of self-report scales is usually a pragmatic choice within this research area.

Three of the studies in this research project were based on student self-reports. Winne (2016) argued that learners frequently have incomplete and biased recollections of their study methods which can hinder their ability to effectively engage in self-regulated learning. This means that students may not accurately remember the study strategies that were previously most effective for them, leading to potential difficulties in planning, monitoring, and regulating their learning in the future. For example, a student may believe that they performed well on a test solely because they spent a lot of time studying, when in fact, their success was due to a specific study strategy used. This incomplete and biased recollection of their study method could result in the student investing more time in studying for future tests, rather than focusing on the specific strategy that led to their success. Consequently, self-report instruments, such as questionnaires, tend to measure broad concepts that can be generalized across time and multiple domains (e.g., cognitive, motivational, emotional, and behavioural states; Muis et al., 2007; Schellings, & Hout-Wolters, 2011), making it challenging to assess students' actual behaviours. As with nearly any psychological instrument the behaviours of respondents will vary over occasions and contexts. Thus, the level of granularity should be considered as it may also effect findings. For example, the DMSL aims to measure students' performance at the course level; however, course level performance may vary across time and context (e.g., this level of granularity is still too large to detect context-dependent variations in motivational belief and learning strategies).

The constructs derived from questionnaires typically reflect what students usually do or what they are predisposed to do, which is different from what students do when engaging in a specific task in a particular context (Marton & Saljo, 1976; Castillo-Diaz & Gomes, 2023). Variation may also be seen in the selection of the reference point within self-report measures both between and within respondents (with individual reference points varying across items and occasions; Veenman & Alexander, 2011). Additionally, some students may under or over-

report their performance (Mayer et al., 2007). Therefore, it would be more accurate to assess students' predispositions to engaging in learning rather than their study actual behaviours via self-reported questionnaires. For example, to determine the amount of effort students are willing to put into studying a particular subject, one consideration could be assessing their prior experiences with the particular subject. Similarly, the level of self-efficacy that a student has for a specific subject depends on their previous experiences with that subject matter. Hence, conducting a study that is specific to a particular course is more likely to yield accurate results in terms of how much effort students are willing to put into studying, and their level of self-efficacy for that course (Rotgans & Schmidt, 2009).

Questionnaires on student learning require respondents to give cumulative and retrospective accounts of their academic tasks, and it is unlikely that they retain an accurate record of the mental activities involved in past tasks (Richardson, 2004). Therefore, it may also be possible that university students answer in a socially desirable way, making some items more transparent than others (Heikkilä & Lonka, 2006). It is important to note that self-report instruments are limited due to their dependence on the credibility of the respondents. It has been recognised that the results of self-report inventories, such as the MAI, should not be used in isolation as a diagnostic tool, but can be a valid and positive addition to the learning and teaching evaluation process (Paulhus & Vazire, 2007). A further limitation of the measures used is that the scales were only partially labelled (with labels at each end of the scale and no labelling in the five intermediate points). Any future study should consider the use of fully labelled scales, as this can reduce satisficing among respondents thus reducing the level of interpretation needed by the respondent (i.e., the score interpretation argument; Krosnick, 2018), thus protecting the measure's validity.

The Psychology department at the University of Liverpool is very heterogeneous in its intake, with approximately 95% of the cohort being young UK nationals and female (with reported levels of disability being similar to other comparable departments; ONS, 2019). Therefore, in all of the current research studies presented (even the DSML) had a far higher percentage of younger and female than male and/or mature respondents. Due to the composition of the student population, it was not possible to make objective comparisons between students based on their demographic characteristics. However having said this the make up of the demographic is similar to other organisations and therefore while results in other groups may show some variation they can be considered typical of those within UK psychology departments. Nonetheless, as the objective of the research is to ultimately utilise the model for new students in comparable or challenging situations, its' validation is crucial across other datasets. A multilevel cross-validation method is therefore suggested in future research to explicitly assesses the applicability of the current administered measures on new students, with new material, and in new communities (Winne & Baker, 2013). According to Wolters and Pintrich (1998), self-report measures have a further limitation in that they may not provide an accurate representation of the wide range of experiences and perspectives present within a particular population, especially when demographic factors specific to the university student body are at play. Additionally, it is important to distinguish between differences in subject areas, overall instructional approaches, and the makeup of the specific institution.

The administered questionnaires were written and completed in English, however for a subset of the sample English was their second or even third language. Thus, they may have interpreted the questions in a different way than a native English speaker. One common mistake a learner might make when answering a questionnaire that is not in their native

tongue is to mistranslate words or phrases from their native language to that of the questionnaire (Borsa et al., 2012). This can result in incorrect or ambiguous responses that do not accurately reflect the learner's intended meaning (Briguglio, 2000). Additionally, learners may struggle with the syntax and grammar of their non-native language, leading to incorrect word order or grammatical errors that can impact the clarity of their responses. These mistakes can significantly affect the data's validity and reliability, making it more challenging to draw meaningful conclusions from the results. Similarly, translation issues can also be seen in the translation of measures into different languages, therefore any future study will need to ensure that a translation retains its originally intended meaning. Equally students with dyslexia may misread or skip over words, leading to incomplete or inaccurate responses, although neither of these possibilities was measured in our sample. A future study might want to measure respondents' comprehension of the study measures to see how understanding differs the resultant findings. For the purpose of this research project, an effort has been made to evaluate the reliability of the DMSL measure with university students from other cultures and languages, for example it has been used in the Kingdom of Saudi Arabia (Alsharif & Limniou, 2020). More work is however needed to establish whether this measure can be used equally and as successfully with students in other languages and contexts.

8.8. Future Directions and Further Practical Implications

Overall, when attempting to understand motivation and engagement in university students, it is critical to consider their wide ranging educational and personal experiences, as well as their overall well-being (Martin et al., 2017). This includes not only academic tasks but also class activities and materials, a sense of belonging at university, and social and emotional development (Pedler et al., 2021; Gillen-O'Neel, 2021; Bergdahl et al., 2018; Gunuc, 2014; Santos et al., 2021). One area of interest is how to improve student engagement and achievement by considering the impact of student well-being on academic success. As this thesis focuses exclusively on academic factors affecting student learning processes future work could look to explore the array of non-academic factors affecting learning and academic engagement and progress (such as poor mental health, financial difficulty, disability, caring responsibilities, and language).

A meta-analysis of 109 studies by Robbins et al., (2004) explored the correlation between academic outcomes in higher education with psychosocial and study skill factors finding both contextual and social factors played an important role in student success. The authors suggested researchers should include factors such as perceived social support, institutional selectivity, and financial support, as well academic factors such as motivation and academic achievement into their measures to better predict academic achievement. The DSML is currently being trialled with some additional questions on health effects (both mental and physical) and other responsibilities (such as work or caring) to further explore these two factors on student experience. The thesis proposes that in order to reach a complete the morning comprehension of teaching and learning it is necessary to examine all elements of the teaching/learning context that may play a role in student outcomes. This includes for example how students describe their perceptions and thoughts about learning including their expectations of it.

The findings from both study one and study five suggest that students were not as prepared for their university experience as they could have been. To address the challenges associated with transitioning from pre-tertiary education to higher education, it is important to promote greater communication and collaboration between these two sectors. While some issues, such as developing independence in learning may be difficult to overcome, universities can work with pre-tertiary schools to provide more opportunities for students to become familiar with the realities of university study before they even apply. This can help to facilitate a smoother transition and ensure that students are better prepared for the demands of higher education. Kitching and Hulme (2013) suggest that increased dialogue between the two sectors could help to build greater awareness of the challenges and issues faced by both parties. According to Crisp et al., (2009), one approach to improving the first-year university experience is to ensure that there is a better alignment between student expectations and the reality of their experience. This can be achieved by either adjusting students' expectations to better match the realities of university life, or by modifying the institution's strategies for engaging with student s to better meet their needs.

Using a few simple design strategies universities could improve students' experiences facilitating successful transitions into tertiary education. In every case, the goal is to establish a stronger connection between students' expectations and their first-year experience. Universities also need to acknowledge and cater to the diversity of students within their teaching and support initiatives. This can be achieved by introducing orientation programs that help students adapt to the new academic environment and by providing personalised support to address specific student needs. For instance, universities can offer language support to students from non-English speaking backgrounds that is specifically tailored to the subject terminology rather than a generic offering that does not take account of subject specific language. They could also consider providing additional resources catering to the learning background of the student. By recognising and addressing the diverse needs of students, universities can facilitate student success both in regard to one's transition and subsequent learning across the degree. One area in which this can be addressed is motivational factors.

Heikkilä and Lonka's (2006) research highlights the crucial role of motivational factors in higher education and emphasises the need to incorporate them into effective teaching and learning strategies. Motivation is often driven by emotional states, such as a desire to achieve a sense of accomplishment or avoid the negative feelings associated with failure. Similarly, emotions can be influenced by motivational factors, such as the interest or engagement a student feels towards a particular subject or task (Arguedas et al., 2016; Valiente et al., 2011; Moriña, 2019). Understanding the interplay between motivation and emotion is crucial for creating effective learning environments and supporting student success. Additionally, as Entwistle and McCune (2004) suggest, the role of emotion in learning should not be overlooked, and a more nuanced understanding of the different emotional states that can impact learning should be integrated into research and teaching practices. Thus, there is a need for the further development of measurement tools to assess the role of positive emotions in learning and to integrate them into the design of effective teaching and learning strategies. For example, a future study looking at student interaction with a VLE could ask students about their positive and negative experiences using the VLE, especially when first introduced to it. As study five demonstrated getting to grips with new technology can be

overwhelming and difficult for some students. Additionally, the use of VLEs in education has been found to promote convergent thinking among students.

According to Martin (2017), formal education is predominantly focused on convergent (and not divergent) thinking. In convergent thinking, learners are expected to arrive at the same solution or answer as others, such as writing an essay on a specific topic or answering an exam question with a closed or open-ended response. This approach is also evident in learning arithmetic, where learners must use the approved method to arrive at the correct answer and show their work to demonstrate their understanding. However, this approach does not allow for critical evaluation of the learning process or cognitive flexibility and discourages student exploration and understanding. Winne and Nesbit (2010) suggest that learners can improve their academic performance by engaging in self-regulated learning. Through tracking their academic progress and analysing the outcomes of their learning engagements, learners become more aware of how to regulate their learning strategies and improve their subsequent academic achievements. In essence, self-regulated learners experiment with different learning techniques over time to enhance their learning processes in addition to their academic outcomes.

There are many ways of achieving self-regulated learning, such as making feedback to learners' needs meaningful and actionable (Pistilli et al., 2014), or leveraging the capabilities of learning technologies such as VLEs (Lee et al., 2019; Wong et al., 2019). With careful design educators can create a more tailored and personalised learning experience for each student, thereby anticipating the values that students attribute to their education. By providing relevant and useful online resources to students, their interests are stimulated (Vanslambrouck et al., 2019) improving student engagement, academic performance, and overall satisfaction with their educational experience (Boyle et al., 2010; Kauffman, 2015; Walkington, 2013). Furthermore, the use of a VLE can allow for personalised interactions with students, allowing for the system to respond in an automated or semi-automated way based on the specific actions of each individual student. Responses can include generating corrective or reinforcing actions to improve a student's academic performance, increasing their participation in the course, and preventing them from withdrawing from the course altogether (Agudo-Peregrina et al., 2015).

As well as contextual factors due to students coming from an increasing diversity of backgrounds, it is important to consider the needs of both traditional students (i.e., supported by student finance, coming straight from school aged 18) and non-traditional students (i.e., mature, care providers, part-time, or international students; Taylor & Ali, 2017). Tett et al., (2017) found positive relationships with staff acted as a protective factor for disengagement from higher education in non-traditional students. However, student diversity does not stop at transition. Student disability and well-being are two important areas of concern for higher education institutions. Disabled students often face unique challenges, such as difficulties accessing physical spaces and materials, communication barriers, and negative attitudes by others towards one's disability (Kilpatrick et al., 2017). These challenges can impact their academic achievement and overall well-being. It is important for universities to provide support and accommodations for disabled students, such as accessible facilities, assistive technology, and individualized support plans. Additionally, universities should create inclusive and welcoming environments that promote the well-being of all students, including those with disabilities. This can include offering mental health services, promoting healthy habits and lifestyles, and creating opportunities for social connection and community building. By

prioritising student disability and well-being, universities can ensure that all students have equal opportunities for success and a positive university experience. This is especially important when considering mental health. While this thesis did not directly examine student mental health it must be recognised that this factor plays a key role in student success. Those who experience poor mental health are more likely to disengage with their learning (Kroska et al., 2017), lack motivation (Mahdavi et al., YEAR; Rehmen et al., 2020), and ultimately fail their classes and/or drop out (Hjorth et al., 2016).

The traditional approach to higher education places too much emphasis on conformity and convergent thinking, which can hinder the development of metacognition. Metacognition is often treated as a curiosity rather than a crucial tool for exploration and understanding in formal education. This framing however results in students only acquiring basic metacognitive skills, stunting their progress. However, research by Hattie et al., (1996) shows that training in study skills such as self-regulation and metacognition can improve student outcomes. To enhance metacognitive development in students, effective interventions should incorporate motivational and contextual support, as well as training in cognitive awareness and study strategies. Moving forward, higher education institutions should prioritize the cultivation of metacognitive skills by providing targeted training programs and support structures that encourage students to reflect on their own thinking and learning processes. Additionally, instructors can integrate metacognitive exercises and strategies into their teaching practices to help students develop a deeper understanding of their own cognitive processes.

Education and human systems are highly complex, requiring a nuanced understanding and approach that takes into account the specific context and circumstances (Van Merrienboer & Kirschner, 2007, 2013; Roediger, 2008). One-size-fits-all solutions are unlikely to be effective in all situations as specific context and circumstances must be accounted for, therefore generalizations must be made with caution. To support student development effectively, there is a need for improved diagnostic and research tools, such as the DSML, that can help educators identify problems early and intervene constructively. Furthermore, creating a positive study environment and promoting students' self-regulation and expectations for success can have a significant impact. These insights suggest that a multifaceted and adaptable approach to education is necessary to promote optimal student outcomes.

Future research should focus on developing diagnostic tools and approaches that enable educators to identify and respond to the diverse learning needs of their students. Such tools could include diagnostic assessments, adaptive learning technologies, and interventions that target specific cognitive or metacognitive skills. Additionally, research could explore the potential benefits of promoting a growth mindset and building students' resilience and self-efficacy, which could enhance their ability to overcome obstacles and persist in challenging academic tasks. In terms of teaching practice, educators should strive to create a positive and supportive learning environment that fosters students' engagement and motivation. This could involve providing timely and constructive feedback, creating opportunities for peer collaboration and discussion, and promoting active learning strategies that encourage students to take ownership of their learning. Additionally, educators should seek to cultivate students' metacognitive skills by encouraging them to reflect on their learning processes, set goals, and monitor their progress. By adopting a multifaceted and adaptable approach, educators can promote optimal learning outcomes for all students, regardless of their individual needs and circumstances.

8.9. Conclusion

In conclusion, this PhD thesis provides valuable insights into the factors that impact student learning and academic success in higher education. The five studies presented in this thesis highlight the importance of considering the impacts of various factors such as prior learning and metacognitive knowledge, digital learning tools, the use of appropriate learning approaches, motivation, and student experiences. The thesis argues that an updated version of Bigg's (1993) 3P model, the 3P2T model, is necessary to account for the changing landscape of higher education, as seen through its technological advancements and diversification of the student population. The 3P2T model can provide a more comprehensive understanding of the factors that influence student learning and success, allowing educators to tailor their approaches to meet the needs of a diverse student body. However, it is essential to acknowledge that the complexity of student success (or failure) is vast and intricate and is still a long way off from being completely understood. The findings of this thesis have important implications for the design and delivery of higher education regarding the development of effective teaching and learning practices that ultimately promote student academic success.

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10. Appendix

10.1. Appendix 1 - Ethical Approval

Study Number	Study Name	Ethics Number	Ethics Granted
1	A-Level	IPHS-396-2016	January 2015
2	VLE	IPHS-411-2016	April 2016
3	MAI	IPHS-535-2016	July 2016
4	DSML	IPHS-1981-2017 & IHPS10899-2021	May 2017 Revalidated February 2021
5	Qualitative focus groups	IPHS-3444-2018	April 2018

Appendix Item 1.1 - A Level Paper, 396

UNIVERSITY OF LIVERPOOL

Health and Life Sciences Committee on Research Ethics (Psychology, Health and Society)

29 April 2016

Dear Maria,

I am pleased to inform you that your application for research ethics approval has been approved. Details and conditions of the approval can be found below:

Reference:	0396
Project Title:	Personal trait and module characteristics
Principal Investigator:	Maria Limniou
Co-Investigator(s):	Dr Sonia Tucci, Dr John J. Downes, Mrs Caroline Hands
Student Investigator(s):	
Department:	
Reviewer:	Dr Franklin Chang, Dr James Cruickshank
Approval Date:	29/04/2016
Approval Expiry Date:	26/04/2019

The application was **APPROVED** subject to the following conditions:

Appendix Item 1.1 - VLE Paper, 411

UNIVERSITY OF LIVERPOOL

Health and Life Sciences Committee on Research Ethics (Psychology, Health and Society)

11 May 2016

Dear Dr Limniou,

I am pleased to inform you that your application for research ethics approval has been approved. Details and conditions of the approval can be found below:

Reference:	0411
Project Title:	VITAL activities and blended learning
Principal Investigator:	Dr Maria Limniou
Co-Investigator(s):	Dr Sonia Tucci, Dr John Downs
Student Investigator(s):	
Department:	School of Psychology
Reviewer:	Dr Michael Humann, Dr Rebecca Lawson
Approval Date:	11/05/2016
Approval Expiry Date:	28/04/2019

The application was **APPROVED** subject to the following conditions:

Appendix Item 1.2 – MAI, 535

Dr Ben Ambridge, Dr Marco Bertamini, Prof Matt Field, Dr Jacqueline Wheatcroft

UNIVERSITY OF LIVERPOOL

Health and Life Sciences Committee on Research Ethics (Psychology, Health and Society)

13 October 2016

Dear Caroline,

I am pleased to inform you that your application for research ethics approval has been approved. Details and conditions of the approval can be found below:

Reference:	0535
Project Title:	Personality, Motivation, and the Learning Process
Principal Investigator:	
Co-Investigator(s):	Ms Caroline Hands
Student Investigator(s):	-
Department:	
Reviewers:	Dr Ben Ambridge, Dr Marco Bertamini, Prof Matt Field, Dr Jacqueline Wheatcroft
Approval Date:	13/10/2016
Approval Expiry Date:	01/07/2020

The application was **APPROVED** subject to the following conditions:

Appendix Item 1.3 - DSML 1981 & 10899

UNIVERSITY OF LIVERPOOL

Health and Life Sciences Committee on Research Ethics (Psychology, Health and Society)

15 September 2017

Dear Ms Hands,

I am pleased to inform you that your application for research ethics approval has been approved. Details and conditions of the approval can be found below:

Reference:	1981
Project Title:	MSLQ-DSML
Principal Investigator/Supervisor:	Ms Caroline Hands
Co-Investigator(s):	Dr Maria Limniou, Dr Minna Lyons, Dr Susanne Voelkel
Lead Student Investigator:	-
Department:	School of Psychology (including DClinPOsych)
Approval Date:	15/09/2017
Approval Expiry Date:	Five years from the approval date listed above

The application was **APPROVED** subject to the following conditions:

Conditions

- All serious adverse events must be reported via the Research Integrity and Ethics Team (ethics@liverpool.ac.uk)

UNIVERSITY OF LIVERPOOL

Health and Life Sciences Research Ethics Committee (Psychology, Health and Society)

18 October 2017

Dear Ms Hands,

I am pleased to inform you that the amendment to your study has been approved. Details and conditions of the approval can be found below:

Reference:	1981 (amendment)
Project Title:	MSLQ-DSML
Principal Investigator:	Ms Caroline Hands
Co-Investigator(s):	Dr Maria Limniou, Dr Minna Lyons, Dr Susanne Voelkel
Student Investigator(s):	-
Department:	School of Psychology (including DClinPOsych)
Approval Date:	18/10/2017

The amendment was **APPROVED** subject to the following conditions:

Conditions

- All serious adverse events must be reported to the Committee within 24 hours of their occurrence, via the Research

Appendix Item 1.5 – Qualitative 3444

Health and Life Sciences Research Ethics Committee (Psychology, Health and Society)

24 May 2018

Dear Dr Limniou

I am pleased to inform you that your application for research ethics approval has been approved. Application details and conditions of approval can be found below. Appendix A contains a list of documents approved by the Committee.

Application Details

Reference:	3444
Project Title:	Expectations and reflections on the facets affecting students' outcomes.
Principal Investigator/Supervisor:	Dr Maria Limniou
Co-Investigator(s):	Ms Caroline Hands, Dr Minna Lyons
Lead Student Investigator:	-
Department:	School of Psychology
Approval Date:	24/05/2018
Approval Expiry Date:	Five years from the approval date listed above

The application was **APPROVED** subject to the following conditions:

Conditions of approval

Appendix Item 1.6 – Data

Data for all of these projects has been shared to the Open Science Framework and can be found here: https://osf.io/w8mup/?view_only=c4690b60db5b450396b28fbd04e6aa05.

10.2. Appendix 2 - Publication List

Submitted and Pending Publication

Hands, C., & Limniou, M. (2023). Expectations and reflections about starting university - a qualitative focus group study with first and third-year psychology students. *Journal of Further and Higher Education,* Volume TBC.

Hands, C., & Limniou, M. (2023). A longitudinal examination of student approaches to learning and metacognition. *Journal of Higher Education Theory and Practice*, Volume TBC.

Current Related Publications

Hands, C., & Limniou, M. (2023). Diversity of strategies for motivation in learning (DSML)—A new measure for measuring student academic motivation. *Behavioral Sciences*. doi:10.3390/bs13040301

Hands, C., & Limniou, M. (2023). How does student access to a virtual learning environment (VLE) change during periods of disruption? *Journal of Higher Education Theory and Practice*, *23*(2). doi:10.33423/jhetp.v23i2.5824

Hands, C., & Limniou, M. (2022). *Why science qualifications should be a pre-requisite for a Psychology degree programmes – a case study analysis from a UK University.* Bingley, UK: High Impact Practices in Higher Education: International Perspectives.

Limniou, M., Varga-Atkins, T., Hands, C., & Elshamaa, M. (2022.). Learning, student digital capabilities and academic performance over the COVID-19 pandemic. *Education Sciences*, *11*(7), 361. doi:10.3390/educsci11070361

Varga-Atkins, T., Limniou, M., Hands, C., Durrani, Z., & Duret, D. (2021). Digital capabilities, study practices and COVID-19 pandemic: A case study of veterinary and psychology undergraduate students in the UK. In *Challenges and Opportunities of Online Learning*, (pp. 221-271).

Limniou, M., Durrani, Z., Hands, C., Duret, D., & Varga-Atkins, T. (2020). A study for University student digital capabilities, independent learning and the COVID-19 lockdown period. In *13th annual International Conference of Education, Research and Innovation*.

Limniou, M., Duret, D., & Hands, C. (2020). Comparisons between three disciplines regarding device usage in a lecture theatre, academic performance and learning. *Higher Education Pedagogies*, *5*(1), 132-147. doi:10.1080/23752696.2020.1797522

Limniou, M., & Hands, C. (2019). A critique of blended learning: Examples from an undergraduate psychology program. In *18th European Conference on e-Learning (ECEL 19)*. Copenhagen, Demark.

Limniou, M., Duret, D., Treharne, R. E., & Hands, C. A. (2019). Use of devices in a lecture theatre, student behaviours and learning variables: An interdisciplinary study. In *University of Liverpool Annual Learning and Teaching Conference*. Liverpool.

Hands, C., & Limniou, M. (2018). Metacognitive changes across a degree. In *University of Liverpool Annual Learning and Teaching Conference*. Liverpool.

Hands, C., & Limniou, M. (2018). Updating the Motivated Strategies of Learning Questionnaire (MSLQ) for students in a digital age (DSML). In *Higher Education Academy Surveys Conference 2018: Insight for Enhancement*. Leeds, UK.

Hands, C., Limniou, M., & Lyons, M. (2018). What can the tracking logs of a VLE tell us about student behaviours and their effects on course outcomes? In *The 3rd Pedagogic Research Conference*. Liverpool.

Hands, C., Limniou, M., & Lyons, M. (2017). Using the 'blend' effectively: Examining the value of providing online resources to students. In *Association for Learning Technology*. Liverpool.

Hands, C., Limniou, M., & Lyons, M. (2017). How much do subject specific A-level results contribute to first-year studies? In *14th University of Liverpool Learning and Teaching Conference*. Liverpool, UK.

Lyons, M., Limniou, M., Schermbrucker, I., Hands, C., & Downes, J. J. (2017). The Big Five, Learning Goals, Exam Preparedness, and Preference for Flipped Classroom Teaching: Evidence from a Large Psychology Undergraduate Cohort. *PSYCHOLOGY LEARNING AND TEACHING-PLAT*, *16*(1), 36-46. doi:10.1177/1475725716680460

Limniou, M., Tucci, S., Hands, C., & Downes, J. J. (2017). Online tests in the learning process: Strategy, examples, grades and challenges. In *Focus on Educational Research: Practices, Challenges and Perspectives* (pp. 1-23).

Other Publications

Donnellan, W., & Hands, C. (2018). Introducing Psychology Stress Busting Workshops. In *Learning and Teaching Conference, 16th Annual Conference*. University of Liverpool.

Donnellan, W., & Hands, C. (2021). Psychology Stress Busting Workshops video, submission for Alastair Pilkington Award. In *Learning and Teaching Conference, 20th Annual Conference*.

10.3. Appendix 3 Study Four DMSL Questionnaire

Table A1. DSML Measure with Adaptations

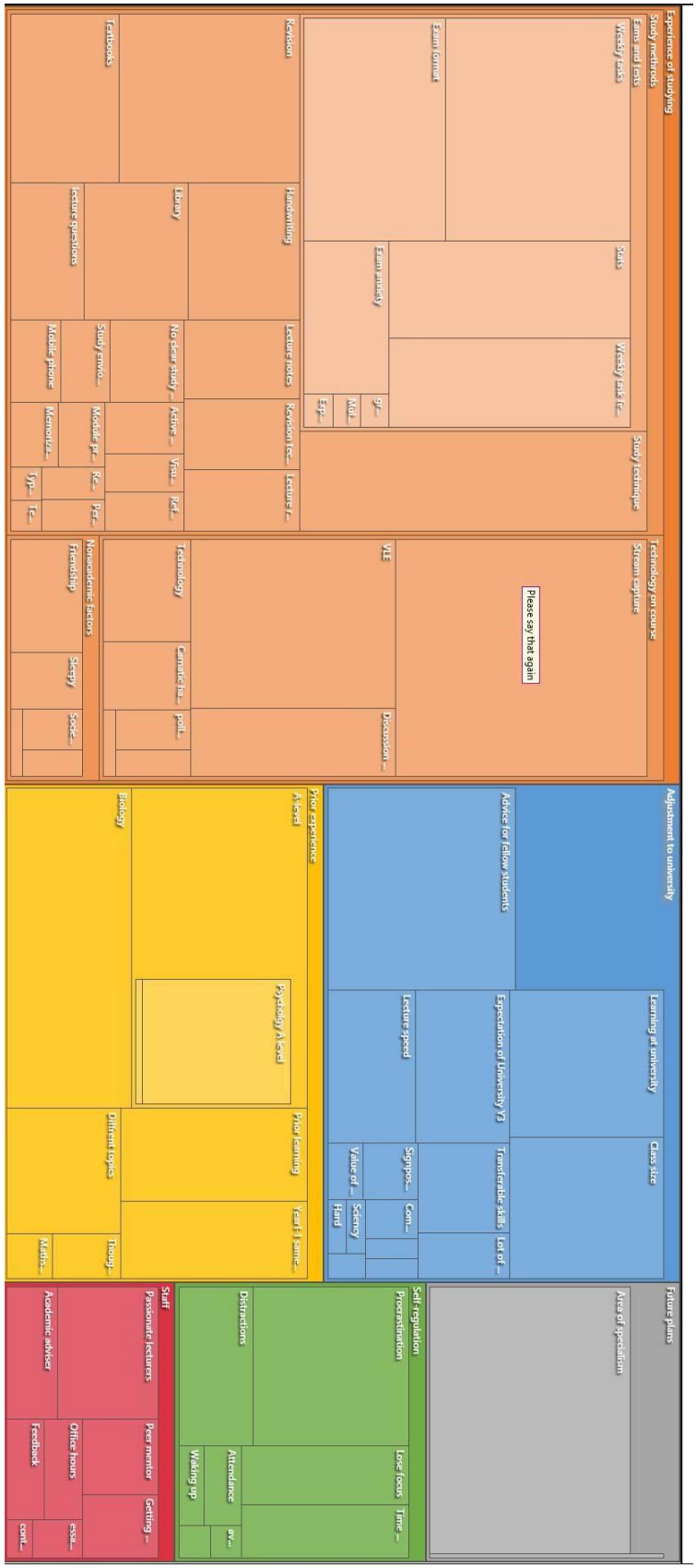
Question	MSLQ	Changed	Final DSML
I like material that really challenges me, even if it is difficult to learn.	1 (SE) & 16 (GO)	Yes	No
I sometimes procrastinate to the extent that it negatively impacts my work.	No—New	N/A	DSML1 SR
When I take a test, I worry about my performance.	14 (TA)	Yes	DSML2 TA
I think I will be able to use what I learn in this course elsewhere in life.	4 (TV)	Yes	DSML3 CU
I believe I will achieve a high grade this year.	5 (SE)	Yes	DSML4 SE
I should begin my coursework earlier than I do.	No—New	N/A	DSML5
I put less effort into studying for classes that I don't enjoy.	No—New	N/A	No
When I take a test, I worry about being unable to answer the questions.	8 (TA)	Yes	DSML 6 TA
I believe I am capable of getting a high mark in this subject.	5 (SE) &21 (SE)	Yes	DSML 7 SE
My goal is to do just enough to pass the course.	No—New	N/A	No
I regularly access the virtual learning environment (VLE), e.g., Blackboard/Vital to look at course material.	No—New	N/A	No
I am confident that I can understand the basic concepts in this course.	12 (SE)	Minor	DSML 8 SE
I take course material at face value and don't question it further.	No—New	N/A	No
When I take tests I think about the consequences of failing.	14 (TA)	No	DSML 9 TA

Question	MSLQ	Changed	Final DSML
I am confident that I can understand the most complex/difficult concepts in this course.	6 (SE) & 15 (SE)	Yes	DSML10 SE
I prefer course material that arouses my curiosity, even if it is difficult to learn.	16 (GO)	Minor	No
I am personally interested in the content of this course.	17 (TV)	Yes	DSML 11 CU
I only access the virtual learning environment (VLE), e.g., Blackboard/Vital when I need to submit an assessment or take a test.	No-New	N/A	No
I have an uneasy, upset feeling when I take a test.	19 (TA)	Minor	DSML 12 TA
I feel that virtually any topic can be highly interesting once I get into it.	No—RSPQ 5	No	No
When course work is difficult, I give up or submit work I know is not my best.	60 (ER)	Yes	No
I work hard at my studies because I find the material interesting.	74 (ER)	Yes	No
I think the material in this course will be useful in my studies.	23 (TV)	MINOR	DSML 13
I make good use of various information sources (lectures, readings, videos, websites, etc.) to help me memorize information.	53 (EL)	Yes	DSML 14
I find the best way to pass examinations is to try to remember answers to likely questions.	No—RSPQ 20	No	No
When studying for this class, I often repeatedly go over the same course material to make sure I understand it.	55 (MC) & 63 (OR)	Yes	DSML15 SS
Sometimes I cannot motivate myself to study, even if I know I should.	No—New	N/A	DSML16 SR
If I use effective study techniques, then I will get a good grade.	No—New	N/A	No
I am not confident that I possess the skills needed to pass this course.	31 (SE) & 29 (SE)	Yes	No
I am motivated to get a good grade to please other people in my life.	30 (GO)	Yes	No
I am motivated to get a good grade for my own satisfaction.	7 (GO)	Yes	No
I make good use of various information sources (lectures, readings, videos, websites, etc.) to help me understand.	53 (EL)	Yes	DSML 17 SD

Question	MSLQ	Changed	Final DSML
During class time I often miss important points because I'm thinking of other things.	33 (MC)	No	DSML 18 SR
Poor grades are largely due to lack of support from my university/instructors.	9 (COL)	Yes	No
If I receive a poor grade, I recognize what I could have done better.	No—New	N/A	No
I make up questions/quizzes to help focus my study.	No—MAI 22	Yes	No
I often feel so bored when I study for this course that I quit before I finish what I planned to do.	37 (ER)	Yes	No
I use the most effective learning strategies in my studies.	No—New	N/A	No
I go back to previously made notes and readings to refresh my understanding of them.	80 (TS) & 42 (OR)	Yes	DSML19 SS
I use the internet to find materials to help support my studies. (Wikipedia, YouTube, social media, etc.)	No—New	N/A	No
For this question, please select: "Not at all true of me".	CHECK	CHECK	CHECK
If I get confused when studying, I take steps to clarify any misunderstandings.	41 (MC)	Yes	No
When studying for this class, I often repeatedly go over the same course material to memorize it.	59 (RE) & 72 (RE)	Yes	DSML20 SS
I work hard to do well in this course, even if I don't like what we are doing.	48 (ER)	No	No
I make simple charts, diagrams or tables to help me organize course material.	49 (OR)	No	No
I treat the course material as a starting point and try to develop my own ideas about it.	51 (CT)	No	No
I find it hard to stick to a study schedule.	52 (TaS)	No	DSML21 SR
When I study for this course, I examine a range of information from different sources (websites, videos, textbooks, journals, etc.).	53 (EL)	Yes	DSML22 SD
Before I study new course material thoroughly, I often skim it to see how it is organized.	54 (SR)	No	No
I ask myself questions to make sure I understand the material I have been studying.	55 (MC)	Minor	No
I often find that I have been studying but don't fully understand the material.	76 (MC)	Yes	No
I find I can get by in most assessments by memorizing key points rather than trying to understand the topic.	No—RSPQ11	Minor	No
I try to relate ideas in this subject to issues in the real world.	No—New	N/A	No

Question	MSLQ	Changed	Final DSML
When studying, I try to relate the material to what I already know.	64 (EL)	Minor	No
When I study for this course, I write summaries of the main ideas presented.	67 (EL)	Yes	No
I try to understand the material in this class by making connections between the different types of information provided (lectures, readings, videos, websites etc.).	53 (EL)	Yes	No
I make sure I keep up with the demands of my course.	70 (Tas)	Yes	No
When presented with a theory or conclusion, I consider possible alternative explanations.	47 (CT) & 71 (CT)	Yes	No
I make lists of important terms or key words for this course and memorize them.	72 (REH)	Yes	No
I study the course materials regularly.	73 (Tas)	Yes	No
I put less effort into studying subjects I find boring and uninteresting.	74 (ER)	Yes	No
Other things in my life tend to take priority over this course.	77 (Tas) & 33 (MC)	Yes	DSML23 SR
I set goals for myself in order to direct my activities in each study period.	78 (MC)	Minor	No
I use an academic database to help find materials to help support my studies.	No—New	N/A	No
I rarely find time to review my notes or readings.	80 (Tas)	Minor	DSML24 SR
My answers are fair reflection of my true feelings.	CHECK	CHECK	CHECK

10.4. Appendix 4 – Study Five Hierarchal Chart



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